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The Finnish Potential Output: Measurement and Medium-term Prospects

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Abstract

In this report, we discuss the measurement of the potential output of the Finnish economy and the potential's medium-term growth prospects.

We apply novel approaches to the estimation of Finland's production function (constant elasticity of substitution, CES) and the filtration of the potential output (Sequential Monte Carlo method, SMC) with the aim of improving the European Commission (EC) production function methodology in mind.

Our results suggest that the cyclical component in the fluctuation of Finland's GDP may have been historically larger than the European Commission method would suggest. We present statistical evidence which supports the replacement of the Cobb-Douglas production function with the more general CES function. The latter function leads to a distinction between labor- and capital-augmenting productivity which matters for the measurement of the potential output: the capital-augmenting productivity tends to develop in a more procyclical manner than the labor augmenting productivity, and the SMC estimation shows that there is negative covariation in the cyclical components.

We further apply the SMC method to estimate the NAWRU and the labor force participation rate as well as their covariation. The results are similar with the EC estimates during the last years, but smoother during the Finnish Great Depression. We find that especially the estimates of NAWRU and the potential labor-augmenting productivity are very sensitive to the real-time uncertainty.

We study the medium-term growth potential of the Finnish Economy in the years 2019–2023 using Etla's multi-sector growth model. We find that the average GDP growth rate produced by the model forecast is 1.5% under the expected trends in technology, demography, and trade. The growth is predominately determined by information technology and the external trade.

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Tiivistelmä

Tämä tutkimus koskee Suomen kansantalouden potentiaalisen tuotannon mittaamistapaa ja potentiaalin kasvunäkymiä keskipitkällä aikavälillä. Tutkimuksen lähtökohtana on Euroopan komission käyttämä tuotantofunktiomenetelmä. Siinä kansantalouden tuotantotapaa kuvataan erilaisten tuotantopanosten ja käyttöteknologioiden yhdistelmänä eli tuotantofunktiona. Eri komponentteihin liittyvät suhdannevaikutukset huomioidaan erikseen kokonaissuhdannevaikutuksen laskemiseksi.

Hankkeessa komission menetelmää kehitetään mallintamalla tuotanto aikaisempaa yksityiskohtaisemmin ns. vakioisen työvoima- ja pääomapanoksen välisen substituutiojouston (CES) tuotantofunktion avulla. Lisäksi tuotantofunktion eri komponenttien suhdanneluonteista vaihtelua arvioidaan uudella Sequential Monte Carlo (SMC) -menetelmällä.

Tutkimuksessa havaitaan, että CES-tuotantofunktio soveltuu paremmin kuvaamaan Suomen kansantalouden tuotantotapaa kuin komission käyttämä yksinkertaisempi ns. Cobb-Douglas -tuotantofunktio. CES-tuotantofunktio mahdollistaa myös eri tuotantopanosten, eli työvoiman ja pääoman, käytön tehokkuuden erillisen arvioinnin. Hankkeessa saatujen uusien tulosten mukaan laskusuhdanne alentaa pääoman käytön tehokkuutta, kun taas työvoiman käytön tehokkuuteen se vaikuttaa vain vähän ja jopa tehostavasti.

Mallinnamme SMC-menetelmällä, paitsi tuottavuussarjojen potentiaalin, myös kansantalouden inflaationeutraalin tasapainotyöttömyyden eli NAWRU:n, sekä työvoiman osallistumisasteen rakenteellisen tason. Viimeaikaista kriisiä koskevat arviomme syklisistä vaikutuksista ovat samansuuntaisia komission aikaisempien arvioiden kanssa, mutta 1990-luvun lamaa koskevat arviot ovat vähemmän myötäsyklisiä.

Kaiken kaikkiaan tuloksiemme mukaan suhdannevaihtelut ovat vaikuttaneet kansantalouden tuotantomäärään jonkin verran enemmän kuin komission menetelmää noudattaen on aikaisemmin arvioitu. Erityisesti NAWRU:n ja työvoiman tuottavuuden reaaliaikainen arviointi on kuitenkin uusillakin menetelmillä vaikeaa ja arviot ovat herkkiä revisioitumaan.

Arvioimme myös kansantalouden potentiaalisen tuotannon kasvunäkymiä vuosina 2019–2023 Etlan sektoritasoisen kasvumallin avulla. Käyttämässämme mallissa teknologisen kehityksen, demografian ja kaupan pitkän aikavälin trendien vaikutuksia arvioidaan yhtenäisessä mallikehikossa. Mallin perusuralla tuotannon volyymikasvu tulee olemaan noin 1,5 % vuodessa seuraavien viiden vuoden aikana. Kasvuun vaikuttavat erityisen voimakkaasti informaatioteknologia ja kansainvälisestä kaupasta syntyvä kasvuvaikutus.

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Sammandrag

I denna rapport analyserar vi mätningen av den finländska potentiella produktionen och potentialens tillväxtutsikter på medellång sikt.

Vi tillämpar nya metoder för att beräkna den finländska produktionsfunktionen (konstant elasticitet för substitution, CES) och filtrering av potentiell produktion (sekventiell Monte Carlo-metoden, SMC) i syfte att förbättra Europeiska kommissionens (EG) metod för att beräkna produktionsfunktion.

Våra resultat tyder på att den cykliska faktorn i den finländska BNP-fluktuationen historiskt sett kan ha varit större än vad Europeiska kommissionens metod antyder. Vi presenterar statistisk bevisning som stöder användningen av mer allmän, CES produktion funktion i stället för Cobb-Douglas. Den uppkomna distinktionen mellan produktivitet som förstärker arbetskraft och kapital har betydelse för mätning av den potentiella produktionen: Produktivitet som förstärker kapital tenderar att utvecklas på ett mer procykliskt sätt än produktivitet som förstärker arbetskraft, och SMC uppskattning visar att det finns en negativ variation i de cykliska komponenterna.

Vi tillämpar vidare SMC-metoden för att uppskatta NAWRU och arbetskraftsdeltagandet och deras samvariation. Potentialen liknar EG-skattningarna under de senaste åren, men smidigare under den finska stora depressionen. Vi finner att särskilt uppskattningar av NAWRU och den potentiella arbets-höjande produktiviteten är mycket känsliga för realtid osäkerhet.

Vi studerar den finländska ekonomins tillväxtpotential på medellång sikt under åren 2019–2023 genom att använda ETLA:s tillväxtmodell för flera sektorer. Vi finner att den genomsnittliga BNP-tillväxten som produceras av modellprognosen är 1,5% under de förväntade trenderna inom teknik, demografi och handel. Tillväxten bestäms huvudsakligen av informationsteknologin och utrikeshandeln.

CONTENTS

TUTKIMUKSEN SUOMENKIELINEN TIIVISTELMÄ

Tämä tutkimus koskee Suomen kansantalouden potentiaalisen eli suhdannevaihteluista riippumattoman tuotantomäärän mittaamistapaa ja potentiaalin kasvunäkymiä keskipitkällä aikavälillä. Potentiaalin laskemisessa tutkimuksen lähtökohtana on Euroopan komission käyttämä tuotantofunktiomenetelmä. Siinä kansantalouden tuotantotapaa kuvataan erilaisten tuotantopanosten ja käyttöteknologioiden yhdistelmänä eli tuotantofunktiona. Menetelmässä määritellään ensin tuotantofunktio ja sen jälkeen kokonaistuotannon suhdanneluonteinen vaihtelu lasketaan perustuen tuotantofunktion eri komponenttien vaihteluun.

Hankkeessa komission tuotantofunktiomenetelmää kehitetään useilla tavoilla. Tuotantofunktio mallinnetaan aikaisempaa tarkemmin ns. vakioisen substituutiojouston (CES) tuotantofunktion avulla. Käytetty CES-tuotantofunktio poikkeaa komission aikaisemmin käyttämästä ns. Cobb-Douglas -tuotantofunktiosta, koska CES-funktion käyttäytymisen kannalta keskeinen (vakioinen) työvoima- ja pääomapanoksen välinen substituutiojousto estimoidaan aineistosta, mutta Cobb-Douglas -funktiota käytettäessä sen arvo perustuu funktion määritelmään. Lisäksi hankkeessa tuotantofunktion eri komponenttien suhdanneluonteista vaihtelua arvioidaan uudella menetelmällä (ns. Sequential Monte Carlo (SMC) -menetelmä). Uusien tarkastelujen avulla saadaan entistä yksityiskohtaisempaa tietoa suhdanteiden vaikutuksesta Suomen kansantalouteen ja toisaalta suhdanteista riippumattoman potentiaalin kehityksestä.

Syitä tulosten tarkentumiseen on useita. Ensinnäkin tutkimuksessa havaitaan, että CES-tuotantofunktio sopii tilastollisesti paremmin kuvaamaan Suomen kansantalouden tuotantotapaa kuin komission käyttämä Cobb-Douglas -tuotantofunktio. Lisäksi CES-tuotantofunktio mahdollistaa eri tuotantopanosten, erityisesti työvoiman ja pääoman, käytön tehokkuuden erillisen arvioinnin. Hankkeessa saatujen uusien tulosten mukaan laskusuhdanne alentaa pääoman käytön tehokkuutta, kun taas työvoiman käytön tehokkuuteen se vaikuttaa vähemmän. Tämä tulos auttaa paremmin ymmärtämään Suomen suhdanteisiin voimakkaasti vaikuttavaa, mutta huonosti tunnettua kokonaistuottavuuden heilahtelua, ja yhdistää sen aikaisempaa enemmän pääoman kapasiteetin käytön vaihteluihin.

Suhdannearvioiden täsmentymiseen vaikuttaa lisäksi myös se, että mallinnamme uudella SMC-menetelmällä tuotantofunktion eri komponenttien suhdannekäyttäytymistä. Uutta tarkastelussa ovat erityisesti eri komponenttien suhdannekäyttäytymisen yhteistarkastelut: Tutkimme CES-tuotantofunktiosta saatujen tuotantopanosten käytön tehokkuuksien ja työvoimapanoksen eri komponenttien yhteisliikettä suhdanteen aikana.

Havaitsemme, että pääomapanoksen käytön suhdanneluonteinen tehokkuuslasku on yhteydessä työpanoksen käytön tehokkuusnousuun. Havainto tukee aikaisempia arvioita työpanoksen rakenteen muuttumisesta suhdanteiden mukana. Työpanoksen potentiaalin arvioimiseksi hyödynnämme mallia, jossa inflaationeutraali tasapainotyöttömyys, NAWRU, arvioidaan yhtäaikaisesti työvoiman osallistumisasteen rakenteellisen tason kanssa. Havaitsemme, että työttömyyden ja osallistumisasteen välillä on yhteinen suhdanneluonteinen komponentti: työttömyyden suhdanneluonteinen kasvu johtaa osallistumisasteen suhdanneluonteiseen laskuun. Muuttujien yhtäaikaisen muutoksen huomiointi voi edesauttaa esimerkiksi inflaation ja suhdanteiden välisen yhteyden parempaa hyödyntämistä suhdannetilanteen arvioinnissa.

Tuloksiemme mukaan suhdannevaihtelut ovat vaikuttaneet kansantalouden tuotantomäärään jonkin verran enemmän kuin komission menetelmää noudattaen on aikaisemmin arvioitu. Tuotantofunktion eri komponenttien suhdanneluonteisen vaihtelun osalta myös uusin menetelmin tuotetut viimeaikaista talouskriisiä koskevat arviot ovat tosin samansuuntaisia komission aikaisempien arvioiden kanssa. Erot ovat sen sijaan suurempia 1990-luvun laman osalta. Uudet potentiaalin arviot riippuvat huomattavasti vähemmän suhdanteista, ja siten uusi menetelmä näyttäisi vähentävän potentiaaliarvioihin liittyvää osittain ongelmallista myötäsyklisyyttä. Toisaalta erityisesti NAWRU:n ja työpanoksen käytön tehokkuuden reaaliaikainen arviointi on uusienkin menetelmien avulla vaikeaa ja arviot ovat herkkiä revisioitumaan.

Osana tutkimusta arvioimme myös kansantalouden potentiaalisen tuotannon kasvunäkymiä vuosille 2019–2023. Hyödynsimme arvioinnissa Etlan sektoritasoista kasvumallia, jossa potentiaalisen tuotannon kasvua ajavien fundamentaalien (tuottavuuskehitys, demografia ja kaupan pitkän aikavälin rakenne) vaikutuksia potentiaaliin arvioidaan yhtenäisessä kehikossa. Investointi ja kulutuskäyttäytymisen oletetaan olevan kuluttajan hyvinvointia optimoivaa ja resurssien olevan tehokkaassa käytössä. Arvion perusteella tuotannon volyymikasvu tulee olemaan noin 1,5 % vuodessa seuraavien viiden vuoden aikana, tosin arvoihin liittyy huomattava määrä epävarmuutta. Kasvuun vaikuttavat erityisen voimakkaasti informaatioteknologia ja kansainvälisestä kaupasta syntyvä kasvuvaikutus.

1 INTRODUCTION

The proper timing and scaling of fiscal policy require detailed information about the cyclical situation of the economy and its longer-term production potential. The objective of fiscal policy is on one hand to respond to changes in the economic cycles: to offset the loss of private economic activity in the downturn and to create new stimulus reserves and help to avoid overheating during the upturns. On the other hand, fiscal policy must also ensure fiscal sustainability, which depends on the development of the production potential of the economy in the longer term.

However, the cyclical nature of various economic shocks and their impact on the long-term production potential is difficult to observe in practice. Potential output, typically defined as the level of output that an economy can produce without triggering above-normal inflation, is an economic concept that has no direct, observable counterpart in the data. The estimation of the potential output and the output gap (i.e. the difference between actual and potential economic activity) requires assessments on several quantities that are difficult to measure. In practice, the potential output is typically identified via the estimation of the low frequency movement of the actual production. The inflation-neutral growth of the economy is assessed by forecasting the low-frequency trend of the economy and then comparing actual economic development to this trend.

Due to both genuine uncertainty and the difficulty of model choice, the potential output estimates are uncertain and often change considerably over time. This uncertainty is costly because it undermines the possibility of a counter-cyclical fiscal policy. It is especially problematic in the European policy context because the statistical estimates of the production potential and the output gap have been given a central role in the EU's fiscal framework (European Commission 2018A). The measurements are used in calculation of one of the most central fiscal policy indicators of the framework: the structural budget balance (see, for example, Mourre et al., 2013; Havik et al., 2014)[1].

Uncertainty will never be completely eliminated, but it is nevertheless an important goal of economic research to find better instruments to measure the potential output and the business cycle, and thus provide better guidance for the fiscal policy.

1.1 Aims of this project

This project develops the methodology for measuring the potential output and assessing the medium-term growth prospects of the Finnish economy by forecasting the potential. We apply novel approaches to the estimation of the Finnish production function (constant elasticity of substitution, CES) and the filtration of the potential output (Sequential Monte Carlo method, SMC) with the aim at improving the European Commission (EC) production function method. Furthermore, we use structural macroeconomic model to estimate the medium-term growth potential of the Finnish economy.

We base our measurement of the potential output on the production function method that is currently used by most economic institutions. Our starting point is the method of the European Commission because of its important economic policy role. The aim of the project is to

1 It measures the government budgetary position when the effect of cyclical fluctuations and one-off expenditure and income items has been eliminated.

Box 1.1 How to measure potential output

With the potential output of an economy, one refers to its output in the hypothetical case in which its output is not distorted by cyclical factors or random fluctuations. The standard definition of the potential is the level of output that an economy can produce without triggering above-normal inflation. The definition is originally introduced by Okun who emphasized that potential output is a "supply concept, a measure of productive capacity." (Coibion et al., forthcoming).

Being a theoretical concept, there is no direct way to measure the potential output, and one may (roughly) distinguish between three approaches to estimating and predicting it (cf. Coibion et al., forthcoming).

In what one could call a (purely) *statistical approach*, one tries to discern the potential output from past output data without introducing any particular theory on the factors which determine it or make the actual and potential output differ. In practice, the potential output is typically identified by estimating the low frequency movement of the actual production. The inflation-neutral growth of the economy is assessed by forecasting the low-frequency trend of the economy and comparing it with actual economic development.

The methods used for measuring the trend are highly diverse (see e.g. Murray, 2014). In the simplest methods one uses univariate time series filters to isolate the variation of the time series that is considered to be due to the business cycle. This approach has merits in providing clear definitions of the business cycle, but it is problematic because the business cycles are not all similar and there is large variation in their frequencies and effects on economic activity. Alternatively, the trend growth can be estimated through multivariate methods based on, for example, the use of inflation (Phillips curve), unemployment (Okun's law), the capacity utilization rate, and many other variables as auxiliary variables. The information used can be filtered by various filters (e.g. Hodrick-Prescott filter, bandpass filter) or other information-selecting methods such as principal component analysis, or the advance aggregation of auxiliary variables into indices.

The large variety of approaches has not yielded a unique solution to the problem of determining the potential output and the output gap. On the contrary, as Murray (2014) and several other studies show, different statistical methods produce varying results on the magnitude of the potential and the gap, and these results can deviate considerably from each other. Since the output gap is never observed in practice, the great unanswered question on trend measurements is related to model selection: on what grounds should the method, trend and eventually the output gap be selected?

Secondly, potential output may be evaluated using the *production function method*. This method is used by many institutions (OECD, IMF, European Commission). Also the methodology of the European Commission (Havik et al., 2014), which makes use of a Cobb-Douglas production function, and the methods which are developed in Chapters 2 and 3 below and which are based on the CES function exemplify the production function approach.

In this approach one aggregates a comprehensive view of the production capacity of the economy (production function) which is based on economic theory and observations of the state of various components. One tries to estimate the output as a function of the inputs (including at least capital and labor) and the measure (or measures) of the productivity of the economy. The potential output may then at each moment of time be defined as the output which corresponds to the equilibrium level of the inputs and productivity at that time. If the actual dependence of output on various inputs and the equilibrium values of the inputs are well-known, this approach can help in estimating the output gap. On the other hand, the more uncertainty there is concerning the correct function and the equilibrium values, the less useful this approach is. In the worst-case scenario, false beliefs about the operations of economic mechanisms during, for instance, financial crises may lead to major biases in statistical inferences.

To avoid the problem of selecting false theoretical foundations for the analysis, the empirical methods are typically constructed in a manner that offers flexibility in the choice of the model. For example, when separating the cyclical component of unemployment and the wage-inflation neutral potential (NAWRU), one may use empirical models which contain various known operating models of the labor market as special cases. However, the flexibility is not without problems. The more flexible a statistical model is, the more choices its user must make between economic theories. When evaluating the results, a statistician must decide whether the financial economic mechanism that are implied by the model are sensible, or whether the result is indicative of the problems associated with the statistical inference.

Thirdly, it is possible to introduce, not just a production function, but a *whole macroeconomic model* for the economy and deduce an estimate of the potential output from it. In this method, the potential output and potential growth projections are obtained by setting some random shocks and frictions to zero. This approach is exemplified by the use of ETLA model in Chapter 4.

Besides the European Commission, the institutions which produce important estimates of potential output include the Congressional Budget Office (CBO) of the USA, the Federal Reserve Board, the International Monetary Fund (IMF) and the OECD. The assessments of the output gap by the Federal Reserve are judgemental (cf. Edge & Rudd, 2012, p. 2) in the sense that they are not based on any particular fixed model, while the methods used by the IMF are different for different countries (cf. de Resende, 2014, p. 24). Both the OECD and the CBO have developed production function methods of their own.

It might be of some interest to contrast the methodology of the European Commission (presented in Sections 2.2 and 2.7 below) with the methods of the CBO (cf. Shackleton, 2018). The CBO method divides the considered economy (i.e., the US as a whole) into six sectors (Nonfarm business, Farm, Household, Nonprofit, Federal government, and State and local government). The potential output is calculated separately and with partly different methods for the different sectors.

Just like the EC method (see Chapter 3 below), the CBO method estimates potential labor supply using estimates of the participation rate, the equilibrium unemployment rate, and the number of working hours per employee. The potential participation rate is estimated separately for 516 groups of people, which differ with respect to age, sex, race or ethnicity, and level of education. These determine the aggregate participation rate (and the number of persons in the labor market) of the economy, when they are combined with population data. Combined with the natural unemployment rate, they also determine the equilibrium labor supply when it is measured in persons rather than in hours.

The potential weekly number of hours worked is estimated for each of the six sectors separately, using a relatively simple regression model. In addition, estimates of the potential employment share in each sector (i.e. the equilibrium share that the employees of a sector have among all employed persons) are used in order to arrive at the potential labor supply of the economy.

The production function is different in different sectors. The most important of the six sectors is the nonfarm business sector, which produces about 75% of the US GDP (Shackelton, 2018, p. 7). Its production function is a familiar Cobb-Douglas function, in which the potential output is determined by the potential labor supply, potential total factor productivity (TFP), and the capital stock. Also the potential TFP is estimated by a relatively simple regression model.

Summing up, the CBO method is (unlike the EC method) based on dividing the labor force into groups and the economy into sectors, for which estimates of potential output are deduced separately. This makes the amount of data that the CBO method uses much larger, but the CBO method is nevertheless much simpler from the point of view of the mathematician, since it does not make use of any mathematical tools which would be as sophisticated as e.g. the Kalman filter which we describe in Section 2.7.

All in all, due to both genuine uncertainty and the difficulty of choosing a proper estimation model, the potential output estimates often change considerably over time (see, for example, Orphanides & Van Norden, 2002; Rünstler, 2002; Planas & Rossi, 2004; Golinelli, 2008; Marcellino & Musso, 2010; Bouis et al., 2012; Kuusi, 2015; Busse, 2016). The application of the Commission method during the Great Recession confirms the rule: The revisions have been large (Busse, 2016; Kuusi, 2018). Essential forms of uncertainty include the uncertainty concerning the value of knowledge which has been accumulated in companies and individuals, and uncertainty concerning their broader operating environment, including institutions and infrastructure. In small open economies such as Finland, the problems of evaluation are particularly important, as the production is heavily influenced by links to foreign economies and the international competitiveness of production. The small open economies may also become more easily subjected to structural shocks as a result of their specialized production structures.

improve the production function method in order to provide better predictions of the potential and output gap in real time, and also more generally make the production function method more suitable for the Finnish economy. The method used by the European Commission raises several problems, and this project addresses a few remedies that aim to improve the functioning of the output gap methodology.

We also use a structural macroeconomic model to project the potential output of the Finnish Economy over the medium term. The considered model is ETLA's multi-sector growth model that incorporates forecasts of total-factor productivity changes, resources of the economy, as well as the conditions for external trade, and it produces a coherent forecast of the economic growth.

1.2 The main contributions

Let us next introduce the main contributions of our analysis. The research outcomes I and II are based on the analysis conducted by the Labor Institute for Economic Research in section 2. The outcomes III and IV are based on the analysis of the Research Institute of the Finnish Economy in sections 3 and 4.

I. We use the constant elasticity of substitution (CES) functions as the production function. This choice is more general than the Cobb-Douglas specification that is used by the European Commission and it allows us to distinguish between changes in labor augmenting productivity and capital augmenting productivity which affect the total factor productivity (TFP). We develop a method for estimating the CES function from data on output, net capital stock, labor hours, wages and the user cost of capital. The estimation is carried out with different choices of the estimation model, and using also other capital and labor input series than the series which stem the plain national accounts data. Our results suggest that the CES production function is more appropriate for the Finnish economy than the Cobb-Douglas production function specification and that the elasticity between capital and labor is considerably smaller than what the Cobb-Douglas function would imply.

II. We find that the distinction between labor augmenting productivity and capital augmenting productivity matters for the measurement of the production potential. The results indicate that capital augmenting productivity tends to develop in a more procyclical manner than the labor augmenting productivity. We show this by applying the European Commission (EC) TFP method individually to the both productivity series. It also turns out that procyclicality of the potential output is reduced when the Cobb-Douglas production function is replaced by a CES function in the Commission's methodology.

III. We apply novel filtration methods in order to further analyze the cyclical sensitivity of the elements of the production function. In particular, we apply the Sequential Monte Carlo (SMC) method to analyze the cyclical co-variance of the labor inputs and the factor-augmenting productivities. In addition to the cross-variation of the different components of the production function, we also use various indicators of the business cycle as well as detailed Phillips curve specifications.

We first apply the SMC method to investigate the potential level of the labor input. While we use the Phillips curve to identify the non-accelerating inflation rate of unemployment, we simultaneously model the cross-variation of the cyclical components of unemployment and the labor-force participation rate, as well as other cyclical factors to jointly identify the business cycle. Furthermore, we augment the EC Phillips curve with true, forward-looking expectations, and the anchored inflation expectations proposed by Rusticelli et al. (2015). In the estimation we use Bayesian estimation with the Commission estimates as the starting point for choosing priors.

We find that the model identifies reasonable estimates for both the NAWRU and the potential level of the labor force participation rate. While the estimates are similar to EC estimates during the Great Recession, we note that our estimates are considerably smoother during the Finnish Great Depression of the 1990s. Thus, our findings provide evidence against large and short-lived variation of the potential labor input during economic crises, which both the EC and the OECD estimates indicate. We find that the results of the model are not very sensitive to the choice of the Phillips curve, while they indicate that the EC methodology may be preferable to the OECD method. Finally, our results indicate that some restrictions to the signal-to-noise ratios of the filters are warranted to ensure that the potential estimates have theoretically desirable properties.

As a second application of the SMC, we analyze the cyclical cross-variation of the capital and labor augmenting productivities. We find empirical evidence for the cross-variation due to the influence of the business cycle: when the capital-augmenting productivity falls due to the business cycle, the labor augmenting efficiency reacts by increasing. The most natural explanation is that when the capacity utilization of capital falls, it is accompanied by layoffs of the workers that tend to increase the average productivity of the continuing workers.

All in all, the results of our SMC analysis suggest that the influence of the business cycle on the Finnish economic activity may have been larger than the European Commission method would suggests. We also find that especially the NAWRU and the labor augmenting efficiency are very sensitive to the real-time uncertainty, and therefore economic policy that is steered based on them should be cautious.

IV. We also consider a structural macroeconomic model of the medium-term growth potential of the Finnish Economy in the years 2019–2023. The considered model is ETLA's multi-sector growth model that incorporates forecasts of total-factor productivity changes, resources of the economy, as well as the conditions for external trade, and it produces a coherent forecast of the economic growth. We show that the baseline growth path of the model and its structural changes are rather well matched with the data in the years 2000 to 2017, which lends credibility to its projections concerning GDP volume growth also in the medium-term.

According to the considered model, the forecasted average growth rate of the GDP volume growth is at 1.5% per annum in the years 2019–2023, when the model is employed with the long-term historical average total-factor productivity growth in the different sectors, the latest population forecasts, as well as the external market that matches with the actual shares of foreign imports in the domestic markets and the structure of the Finnish exports. By using counterfactual scenarios, we find that the economic growth is predominately determined by the technological improvements in the information and communications technology and the external trade. Finally, as the prior analysis of the labor and productivity potential suggests that they are frequently and heavily revised, we discuss growth scenarios with alternative productivity and employment paths. We find that there is a large variation in the possible potential growth rates of the Finnish Economy over the medium term.

2 CES AGGREGATE PRODUCTION FUNCTION AND THE OUTPUT GAP

Sami Jysmä and Ilkka Kiema

2.1 Introduction

The production function methodology which the European Commission uses for calculating output gaps is based on the Cobb-Douglas production function. The main elements of the method are (1) the filtration of the observed total factor productivity (TFP) to its trend and cyclical components and (2) the analogous filtration of the observed labor supply. This section considers the Constant Elasticity of Substitution (CES) production function as an alternative to the Cobb-Douglas function, and discusses the former filtration (1) of the Commission in the context of the both functions. Chapter 3 discusses alternative filtration methodologies.

Intuitively, the elasticity of substitution governs the substitution between capital and labor when the relative price of the inputs changes. The CES production function is more general than the Cobb-Douglas specification that is used by the European Commission. One may think of the Cobb Douglas function as the special case of the CES production function in which elasticity of substitution is exactly such that the nominal cost shares of the different factors remain constant.

The generalization matters for several reasons. First, it turns out that the Cobb-Douglas function is not very suitable for Finland, and hence, by using the CES function, we avoid the possible errors that are due to the misspecification of the production function. Second, the CES class allows a distinction between labor augmenting productivity and capital augmenting productivity. This contrasts with the single total factor productivity (TFP) series of the Cobb Douglas production function. As TFP is a key factor behind the movements of the potential output as well as the output gap, while its movements are still not very well understood, the distinction allows us to unravel the TFP black box.

We develop a method for estimating the CES function from data on output, net capital stock, labor hours, wages and the user cost of capital. The estimation is carried out with different choices of the estimation model, and using also other capital and labor input series than the series which stem from the plain national accounts data. Our results suggest that the Cobb-Douglas production function specification can be rejected and that the elasticity between capital and labor is considerably smaller than what the Cobb-Douglas function would imply. The results indicate that capital augmenting productivity tends to develop in a more procyclical manner than the labor augmenting productivity. We show this by applying the European Commission TFP method individually to both productivity series. It also turns out that procyclicality of the potential output is reduced when the Cobb-Douglas production function is replaced by a CES function in the Commission’s methodology.

2.2 The Cobb-Douglas and the CES production function

Formally, the production function used by the European commission is the familiar Cobb-Douglas function which may be written as

(1) $$Y = AL^{\alpha}K^{1-\alpha}$$

where Y is GDP, K is capital, L is labor, and A is total factor productivity. It is assumed that the factors of production L and K have the (trend) efficiencies E_L and E_K, but their actual contributions to the output is affected also by their degrees of utilization, U_L and U_K. More precisely, the commission's methodology assumes that the output Y is given by (Havik et al., 2014, p. 10)

(2) $$Y = (U_L LE_L)^{\alpha}(U_K KE_K)^{1-\alpha} = \left(E_L^{\alpha}E_K^{1-\alpha}\right)\left(U_L^{\alpha}U_K^{1-\alpha}\right)L^{\alpha}K^{1-\alpha}$$

so that the total factor productivity may be written as

(3) $$A = PC$$

where

(4) $$P = E_L^{\alpha}E_K^{1-\alpha}$$

expresses the trend component and

(5) $$C = U_L^{\alpha}U_K^{1-\alpha}$$

expresses the cyclical component of the total factor productivity.

The Cobb-Douglas production function does not allow for distinguishing between the effects that changes in the two efficiency factors, E_L and E_K, have on total factor productivity. As we shall see in Section 2.5. below, the production function methodology of the European Commission uses capacity utilization data for estimating the cyclical component C, but the method does not allow one to distinguish between variations in the two degrees of utilization, U_L and U_K which determine C. However, both distinctions can be drawn meaningfully in the context of the constant elasticity of substitution (CES) production function.

The CES production function was first introduced into the literature by Solow (1956, p. 77), who famously drafted the function in order to "provide one bit of variety" into his theoretical investigation of economic growth. Five years later the production function was named and further refined by Arrow et al. (1961), who also were the first to apply the function in an empirical setting. In its original form, the CES function could be written simply as (cf. Arrow et al., 1961, p. 230)

(6) $$Y = \left(aK^{p} + bL^{p}\right)^{1/p}$$

Its defining characteristic, constant elasticity of substitution, means (see Klump et al., 2012, p. 773) that the elasticity of capital intensity K/L with respect to

$$\frac{\partial Y/\partial L}{\partial Y/\partial K}$$

stays constant. More specifically, this elasticity has the value

$$\sigma = \frac{1}{1-p}$$

The Cobb-Douglas production function can be viewed as the limiting case of (6) in which *p* approaches 0 so that, the elasticity of substitution σ approaches σ=1 (cf. Arrow et al., 1961, p. 231).[2] Unlike the Cobb-Douglas function, the function (6) allows one to separate capital augmenting and labor augmenting changes of the production function, as these may be represented as changes in *a* and *b*, respectively. However, the parameters *a* and *b* of the function (6) lack any obvious economic interpretation, and their values will depend on the choice of units for capital and labor. The normalization procedure which was suggested in Chirinko et al. (2011) and Klump et al. (2007) provides a more intuitive formulation for the CES function, and it leads to an estimation procedure for it. Introducing the multipliers X_t and B_t as representations of the capital augmenting and labor augmenting technological change, the normalized production function may be written as (cf. Klump et al., 2012, p. 779)

(7) $$Y = F(X,K,B,L) = Y_0\left[\pi_0\left(\frac{X}{X_0}\frac{K}{K_0}\right)^{-\rho} + (1-\pi_0)\left(\frac{B}{B_0}\frac{L}{L_0}\right)^{-\rho}\right]^{-\frac{1}{\rho}}$$

Here *Y* is production, *K* is the stock of capital, *L* the flow of labor hours, and ρ and π_0 are parameters. The factor substitution parameter ρ is related to the elasticity of substitution via

(8) $$\rho = \frac{1-\sigma}{\sigma}$$

It is obvious that if the combination $X = X_0$, $K = K_0$, $B = B_0$, $L = L_0$, corresponded to the actual values of *X*, *K*, *B*, *L* at some point of time *t* = 0, the value of *Y* which the production function (7) yields for *t* = 0 would be $Y = Y_0$. Hence, we may think of the set $\{Y_0, X_0, K_0, B_0, L_0\}$ as the normalization point of the function F. Also the parameter π_0 has now a clear interpretation: formula (7) implies that if both capital and labor earned their marginal products at the normalization point, the capital income share would at that point be

(9) $$\frac{(\partial Y/\partial K)_0 K_0}{Y_0} = \pi_0$$

and the labor income share would be

$$\frac{(\partial Y/\partial L) L_0}{Y_0} = 1-\pi_0$$

(For a proof, see Appendix.)

The estimates of σ have been seen to convergence across studies. In particular, according to two recent surveys on the subject, the evidence points to a substitution elasticity of 0.4–0.6 for the U.S. economy (Chirinko, 2008) and similar values for a number of other de-

2 To prove this directly, on should express the CES production function (6) in the form $Y/\gamma = \left(\delta K^p + (1-\delta)L^p\right)^{1/p}$, take logarithms and use l'Hôpital's rule in the limit in which $p \to 0$.

veloped countries (Klump et al., 2012). In the case of Finland, to the best of our knowledge, there exists three publications that have estimated the elasticity with Finnish data: Ripatti & Vilmunen (2001), Jalava et al. (2006) and Luoma & Luoto (2010), with substitution elasticity estimates of around 0.6, 0.4–0.5 and 0.5 respectively.

2.3 An estimation procedure for the normalized CES function

As our next step, we shall specify an estimation procedure for a CES function of the form (7). We assume that the observed values K_t, L_t, and Y_t are available at some points of time $t = 1,...,T$. Following the lead of Klump et al. (2012), we shall not choose $t = 0$ to correspond to some actual point of time for which observations are available. Rather, we define $X_0 = \overline{X}, K_0 = \overline{K}, B_0 = \overline{B}$ and $L_0 = \overline{L}$ where $\overline{Z}$ denotes the sample geometric mean of each series Z_t. It immediately follows from these definitions and (7) that

$$F(\overline{X}, \overline{K}, \overline{B}, \overline{L}) = Y_0$$

However, this formula does not provide us with a method of estimating Y_0, since due to the nonlinearity of the CES function, $F(\overline{X}, \overline{K}, \overline{B}, \overline{L})$ is not necessarily identical with $\overline{Y}$ (the geometric mean of the observed outputs). Accordingly, we now introduce a multiplier ζ which connects Y_0 and $\overline{Y}$ via

(10) $$Y_0 = \zeta \overline{Y}$$

Analogously with our earlier characterization (9) of π_0 we now define

$$\pi_t = \frac{\left(\partial Y / \partial K\right)_t K_t}{Y_t}$$

when $t = 1,...,T$ and when $\left(\partial Y / \partial K\right)_t$ is calculated for the values $X = X_t$, $K = K_t$, $B = B_t$ and $L = L_t$, which correspond to the point of time t. This definition means that the income shares of capital and labor at time t would be π_t and $1 - \pi_t$ if they both earned their marginal products. It can also be shown that

(11) $$\overline{\pi} = \pi_0 \zeta^{-\rho}$$

and that

(12) $$\overline{1-\pi} = \zeta^{-\rho} - \overline{\pi}$$

where $\overline{\pi}$ is the geometric mean of the capital share π_t when $t = 1,...,T$ and similarly, $\overline{1-\pi}$ is the geometric mean of the labor share $1 - \pi_t$ (see Appendix for derivations of the above results). Combining (7), (10), and (11), we now write the estimable version of our production function as

(13) $$Y_t = \overline{Y} \left[\overline{\pi} \left(\frac{X_t}{\overline{X}} \frac{K_t}{\overline{K}} \right)^{-\rho} + (\zeta^{-\rho} - \overline{\pi}) \left(\frac{B_t}{\overline{B}} \frac{L_t}{\overline{L}} \right)^{-\rho} \right]^{-\frac{1}{\rho}}$$

We shall assume that there is a markup factor μ_t which is due to imperfect competition and which reduces the income share of both capital and labor. Our representation of the markup is somewhat more general than the one in e.g. Ripatti & Vilmunen (2001, p. 18), in which the markup is represented by a constant factor, since in our model the markup is allowed to depend on time $t = 1,...,T$. Letting r_t be the average user cost of capital and w_t the average hourly compensation of employees, we assume that

(14) $$(1+\mu_t)r_t = \frac{\partial Y}{\partial K} ,$$

and

(15) $$(1+\mu_t)w_t = \frac{\partial Y}{\partial L}$$

When these assumptions are valid, π_t is given by

(16) $$\pi_t = \frac{r_t K_t}{r_t K_t + w_t L_t}$$

just like under perfect competition. Plugging the assumptions (14) and (15) into (13), taking logs and rearranging, it turns out that

(17) $$\ln \frac{r_t K_t}{w_t L_t} = \ln \frac{\bar{\pi}}{\zeta^{-\rho} - \bar{\pi}} - \rho \ln \frac{K_t / L_t}{\bar{K} / \bar{L}} - \rho \ln \frac{R_t}{\bar{R}}$$

where by definition

(18) $$R_t = \frac{X_t}{B_t}$$

and, in accordance with our earlier convention, $\bar{R}$ is the geometric mean of the values R_t. (For proofs, see Appendix.)

We shall estimate (17) with a Kalman filter, viewing $\ln\left(r_t K_t / \left(w_t L_t\right)\right)$ as an observable signal and $\ln R_t$ as the unobserved state. We shall test five specifications for the state equation which connects the current state with past states. Given (17), our Kalman filter models can be expressed in the form

(19) $$\begin{cases} \ln \frac{r_t K_t}{w_t L_t} = \chi - \rho \ln \frac{K_t / L_t}{\bar{K} / \bar{L}} - \rho \ln R_t + u_t \\ \ln R_t = \sum_{i=1}^{\tau} \psi_i \ln R_{t-i} + v_t \end{cases} ,$$

where u_t and v_t are white noise terms. Our approach is to view the χ and ρ as the parameters of the signal equation in each of the model versions that we consider. If we define ϕ by

(20) $$\phi = \chi - \left(\ln \frac{\bar{\pi}}{\zeta^{-\rho} - \bar{\pi}} + \rho \ln \bar{R} \right)$$

the assumptions (17) and (20) imply that $\phi = 0$ for the (unknown) correct values of estimated parameters and the series R_t. We shall view ϕ as a measure of (one type of) inaccuracy in our approach. As will be seen below, the value of ϕ will be rather small for the estimaes that we choose to use.[3]

We consider four autoregressive models, the AR(τ) models with τ = 1, 2, 3, 4, and a model in which the state $\ln R_t$ follows a random walk. (Also the random walk model can be put in the form (19) if one chooses τ = 1 and does not view ψ_1 as an adjustable parameter but stipulates that ψ_1 = 1.) In what follows we shall use maximum likelihood estimates for the parameters χ, ρ, and ψ_i.

Solving (13) for labor augmenting productivity B_t we now conclude that

$$(21) \qquad \ln\frac{B_t}{\overline{B}} = \ln\frac{Y_t}{\overline{Y}} + \frac{1}{\rho}\ln\left[\overline{\pi}\left(\frac{R_t}{\overline{R}}\frac{K_t}{\overline{K}}\right)^{-\rho} + (\zeta^{-\rho} - \overline{\pi})\left(\frac{L_t}{\overline{L}}\right)^{-\rho}\right]$$

and from the definition (18) of R_t, we get

$$(22) \qquad \ln\frac{X_t}{\overline{X}} = \ln\frac{R_t}{\overline{R}} + \ln\frac{B_t}{\overline{B}}$$

Hence, we can acquire estimates also for $\ln\frac{B_t}{\overline{B}}$ and $\ln\frac{X_t}{\overline{X}}$ from the estimation of system (19). Their changes correspond to changes in labor-augmenting and capital-augmenting productivity, and as it will be seen in Section 2.7 below, they can both be viewed as containing a technology-based and a cyclical component.

2.4 Data

Our data stems from Statistics Finland with the exception of the EU-KLEMS data on capital stocks which is used as point of comparison in Section 2.6, and the data from the European Commission which relates to the methods of estimating output gaps that we consider in Section 2.7 below. Since our method of estimating the production function is based on labor share and capital share, we find it more natural to use value added (rather than GDP) as our measure of output of the economy.

We shall use both quarterly and yearly data for the period from 1990 to 2017. We use quarterly data, which has been adjusted seasonally and per working day, on the value-added, labor hours and the wage sums ranging from the first quarter of 1990 to the final quarter in 2017, all obtained from Statistics Finland. The calculations in Section 2.5, which form our benchmark case for choosing between different variants of (19), use net capital stock, as reported in the national accounts by Statistics Finland, as the measure of the amount of capital. In Section 2.6 we shall consider variety of alternative measures for the productive capital stock and for labor input.

We interpolate each yearly aggregate capital stock series to quarters using the *Denton-Cholette method*, which is based on minimizing the sum of squares of the proportional deviations of the first differences between the considered yearly series and an indicator series (Dagum & Cholette, 2006; Denton, 1971). We take our indicator series to be a constant

3 As the equation (20) indicates, one may think of ϕ as the discrepancy between two estimates that our model yields for the same quantity, the constant of the signal equation. The order of magnitude of this constant is -0.70 and hence, in the specifications AR(1)-AR(3) the discrepancy turns out to be less than 0.02 %.

series, implying that our procedure minimizes the squared quarterly changes in the capital stock, subject to the constraint that the yearly average capital stock (calculated from the interpolated quarterly series) equals the yearly capital stock (taken from the yearly data).

For constructing the user cost of capital, we use Statistics Finland quarterly investment goods and value-added deflators, a quarterly series for the interest rate on Finnish government 10-year bonds from the Bank of Finland, and an estimated quarterly depreciation rate of capital. Also these series extend over the period from 1990Q1 to 2017Q4 which we consider. We estimate the average quarterly depreciation rate by using both the net capital stock series and a series for aggregate investment expenditure and by assuming a perpetual inventory with a constant geometrical depreciation rate. More specifically, we estimate the average quarterly depreciation δ rate from the equation

$$K_{t+1} = (1-\delta)K_t + (1-\frac{\delta}{2})I_t + \varepsilon_t, \tag{23}$$

in which K_t is the quarterly capital stock, I_t is the quarterly investment and ε_t is an error term in the period *t*. Moreover, we apply the Hall-Jorgenson formula for the real user cost of capital r_t without accounting for taxes, so that

$$r_t = \left((1+i_{10,t})^{\frac{1}{4}} - 1 - \pi_{inv,t} + \delta \right) \frac{p_{inv,t}}{p_t}, \tag{24}$$

where $i_{10,t}$ is the interest rate on 10-year Finnish government bonds, $\pi_{inv,t}$ is the quarter-on-quarter inflation rate of investment goods, δ is the estimated quarterly depreciation rate, $p_{inv,t}$ is the investment goods deflator and p_t is the value-added deflator.

2.5 Choosing the model specification

We estimate system (19) as a Kalman filter by maximum likelihood. Table 1 shows the estimation results for five different specifications of development of the state variable $\ln R_t$, which expresses the ratio of capital-adjusting and labor-adjusting productivity. We consider non-restricted autoregressive processes of orders one to four (which correspond to (19) with τ = 1, 2, 3, 4) and a random walk process (which corresponds to τ = 1 and ψ_1 = 1.) We report in Table 1 the values of the parameters of the model (19), *p*, and ψ_1,... ψ_τ, as well as the elasticity of substitution σ (which is determined by (8)), the multiplier ζ (which is defined by (10) and which can be solved from (12)) and the discrepancy ϕ which is defined by (20).

Given Table 2.1, we discard the random walk specification as an outlier. We observe that, judged by information criteria AIC, the most successful model is AR(4), while the model AR(1) seems to be most successful when judged by BIC.[4] However, the "discrepancy term" $\ln \phi$ is much larger for the AR(4) model than for the simpler autoregressive models. We shall go for simplicity and use the AR(1) specification in our main calculations.

As Figure 2.1 indicates, the time development of $\ln R_t$ (the capital vs labor productivity ratio) is qualitatively similar in the four autoregressive models (and the models AR(2) and AR(3)

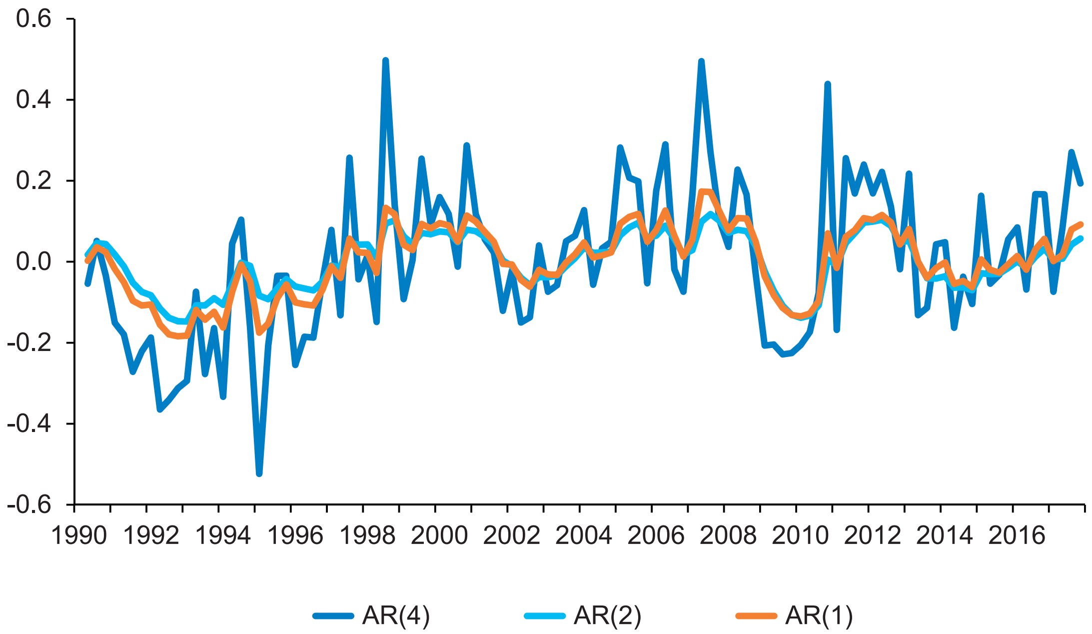
4 The Akaike information criterion (AIC) and the Bayesian Information criterion (BIC) are used for addressing the problems of overfitting which an excessive number of parameters causes in a statistical model. Their values depend on the log likelihood and the number of parameters of the considered model. In comparison with AIC, BIC gives a larger weight to the simplicity (understood as a small number of parameters) as a criterion of model choice.

Table 2.1 Estimation results for the CES-based system

	Specification				
	AR(1)	AR(2)	AR(3)	AR(4)	Random walk
ρ	2.751 (1.246)**	3.215 (1.104)***	3.219 (1.099)	2.263 (1.459)	-0.101 (2.125)
σ	0.267	0.237	0.237	0.306	1.113
ζ	0.927	0.9148	0.915	0.939	1.003
ϕ	-0.000102	-0.000068	-0.00008	0.002124	0.030182
ψ_1	0.841 (0.088)***	1.719 (0.179)***	0.9847 (1.310)	0.305 (0.139)**	1 (f)
ψ_2	0 (f)	-0.787 (0.165)***	0.4837 (2.151)	0.067 (0.094)	0 (f)
ψ_3	0 (f)	0 (f)	-0.5838 (0.9531)	0.037 (0.146)	0 (f)
ψ_4	0 (f)	0 (f)	0 (f)	0.323 (0.130)**	0 (f)
Log-likelihood	-45.225	-44.026	-44.054	-40.359	-52.243
AIC	0.905	0.901	0.901	0.871	1.013
BIC	1.027	1.048	1.091	1.067	1.111

Notes: Standard deviations in parentheses, "f" stands for a fixed coefficient.
Significance levels: * 10%, ** 5%, *** 1%.

Figure 2.1 Capital / labor productivity ratio, log levels. AR(3) is indistinguishable from AR(2).



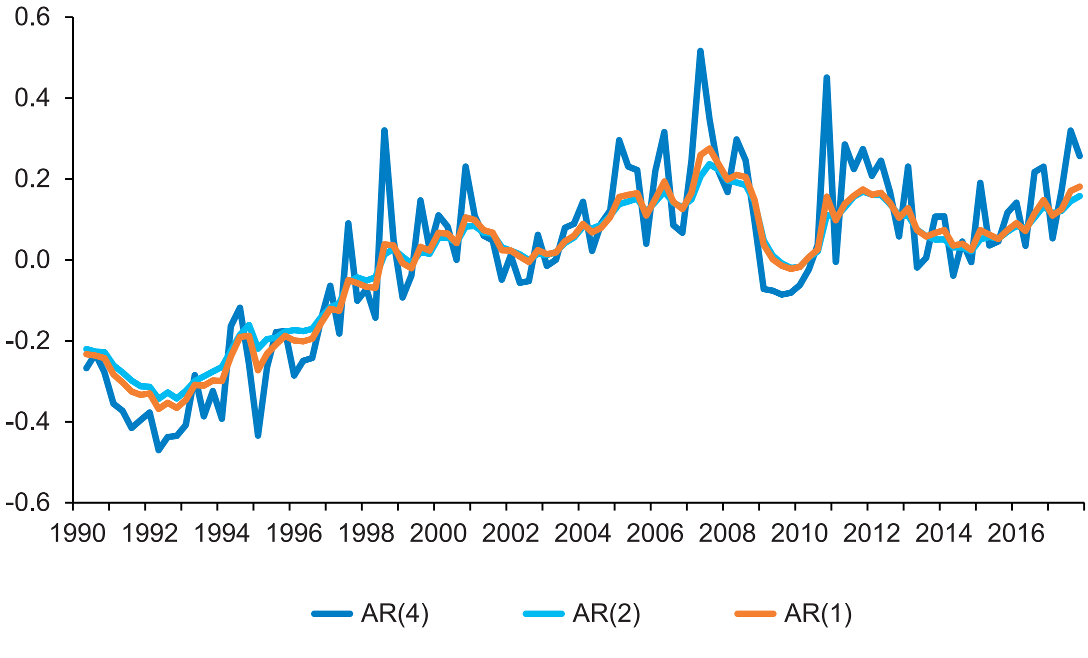
are indistinguishable in the figure), but the model AR(4) produces essentially larger fluctuations for R_t. The point estimate for the elasticity of substitution in the autoregressive cases is around 0.25–0.30, suggesting fairly inelastic substitution between capital and labor. This is slightly out of the range of the findings in the previous studies conducted with Finnish data (estimates range from 0.4 to 0.6).[5] However, both the sample period and the methodology differ from the previous studies. Importantly, the factor substitution parameter ρ differs significantly from 0 in the first two autoregressive cases, implying that the substitution elasticity σ differs from the Cobb-Douglas case of $\sigma = 1$.

The point estimates of the AR-specifications are all weakly stationary, i.e. all the solutions to the characteristic equations of the AR-specifications lie outside the unit circle. Since the random walk specification has a considerably lower fit in terms of log-likelihood than the other cases, and the other cases are all stationary, our results suggest that the underlying process $\ln R_t$ has been stationary at least within this sample period – naturally assuming the model is correct.

Figures 2.2 and 2.3 show the capital and labor augmenting series for the AR-specifications. As it can be seen from the figures, the series for the AR(1), AR(2) and AR(3) specifications trend closely together, but the AR(4) specification shows essentially larger fluctuations than the three other series.

We also note that the cyclical properties of the labor and capital augmenting series seem rather different. Figure 2.4 contrasts GDP growth (more precisely, the change in quarterly GDP which has been seasonally and per-working-day adjusted, when the point of comparison is the same quarter of the previous year) to the change in labor and capital augmenting productivity. (More precisely, the changes in productivity of Figure 2.4 are changes in the quarterly log levels in comparison with the same quarter of the previous year, and they have

Figure 2.2 Capital augmenting productivity, log levels. AR(3) is indistinguishable from AR(2).



5 Cf. Ripatti & Vilmunen (2001), Jalava et al. (2006) and Luoma & Luoto (2010); see also Section 2.1 above.

been calculated using the AR(1) specification.) Figure 2.4 suggests that the capital augmenting series is prone to procyclical swings, whereas the labor augmenting series appears to be slightly countercyclical. We shall provide some further discussion of the countercyclicality of the labor augmenting series and the other cyclical properties of the two series in Section 2.7, in which we shall present our formal tools for separating the cyclical and trend components of the two series.

Figure 2.3 Labour augmenting productivity, log levels. AR(3) is indistinguishable from AR(2).

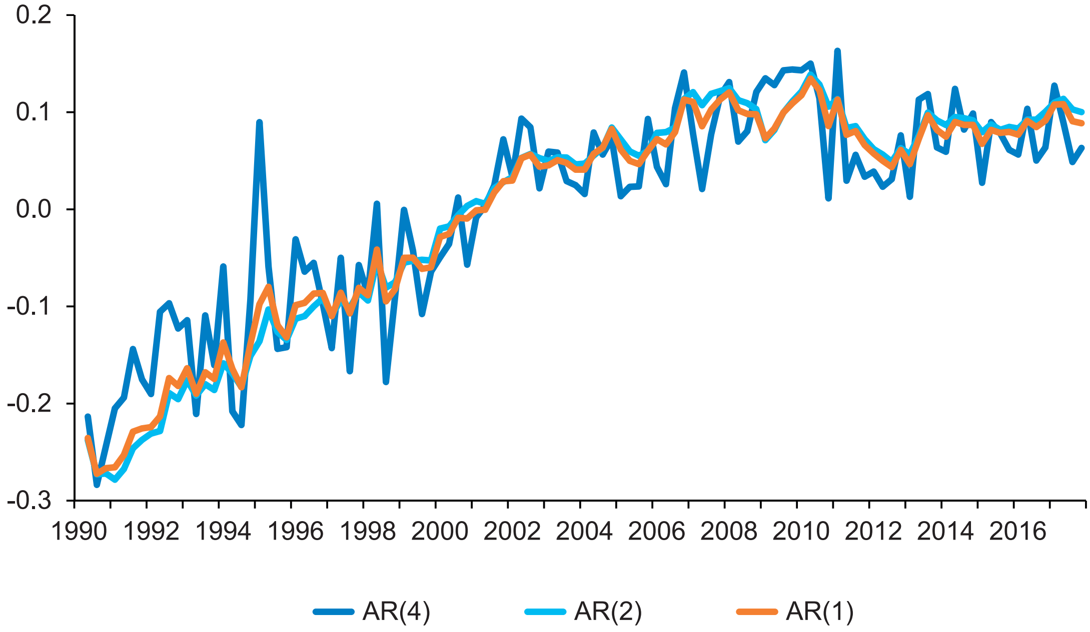
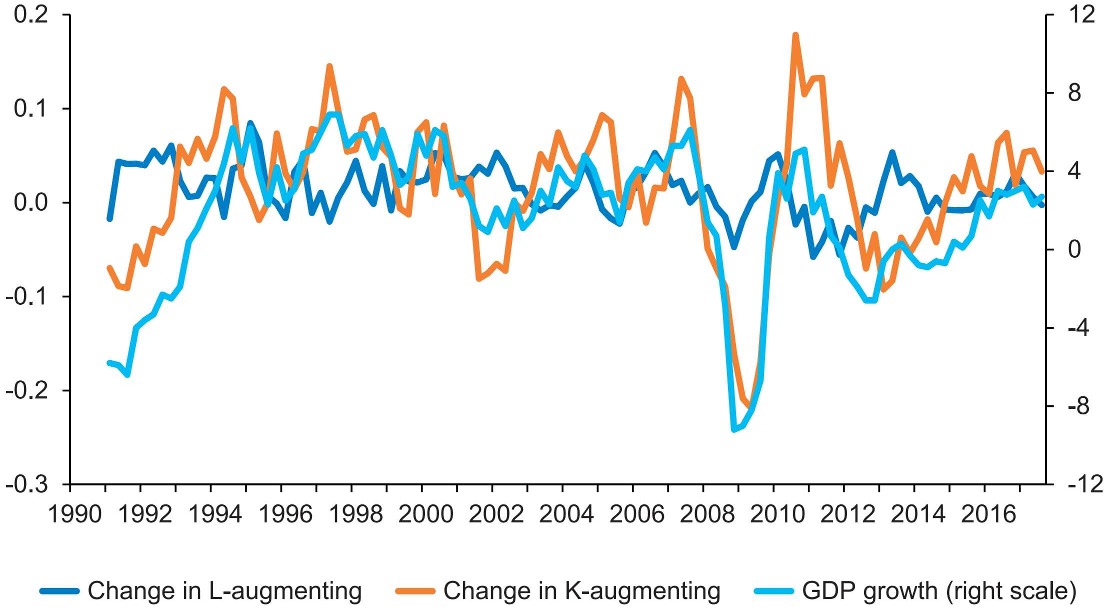


Figure 2.4 Capital and labor augmenting productivity change vs economic growth



2.6 Heterogeneity of productivity within the input series

Neither the aggregate capital stock series K_t nor the labor hours series L_t used in the previous section take into account the presumably large differences in productivity between their individual components (i.e. different types of capital, and work performed by persons with different educational backgrounds). The changes in labor and capital productivity that we analyzed above is, most likely, partly due to changes in the share of various types of capital and labor within the whole capital stock and within the totality of hours worked.

Instead of trying to catch all this heterogeneity within the productivity series, we shall now approach our problem from another perspective and try to take into account some of the changes in productivity already in the factor input series themselves. From the view point of potential output estimation, it would be especially attractive to catch some part of structural productivity change within the input series. This would presumably lessen the amount of residual productivity that has to be divided into trend and cycle components in some fashion.

A method for assessing the productivity contributions of various types of capital and labor is readily available. This method is due to the *EU-KLEMS project*, and also Statistics Finland uses the KLEMS methodology in the estimates of productive capital and labor that its productivity survey yields.[6] The data from the productivity survey and the EU-KLEMS project become available with a considerable lag. For example, in October 2018 the newest data available was 2016 and 2015 for the Productivity Survey and the EU-KLEMS project respectively. This can be a major drawback for a decision maker.

The long lags seem to be due to the large set of classes of capital items that the Statistics Finland productivity survey and the EU-KLEMS project consider. For example, the productivity survey has 14 investment categories in 63 industries and the EU-KLEMS project has 10 investment categories in 34 industries, totaling 882 and 340 categories, respectively. Due to the large number of categories, the construction of the series needs very detailed data, and hence, the series are updated with a long lag.

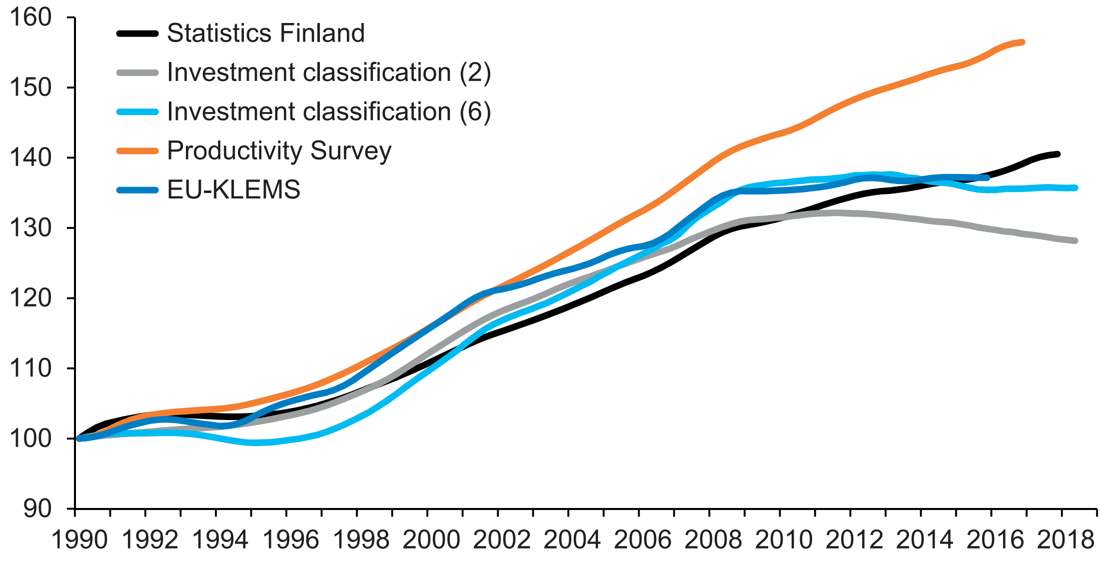
Below we shall follow the KLEMS methodology for constructing productive capital and labor series of our own. We shall construct two series of capital input, and we shall contrast them with the series from Statistics Finland as well as from the EU-KLEMS project. Our series are based on simpler classifications of capital, which allow us to calculate a productive capital measure on the basis of (more quickly available) quarterly national accounts data. We shall also experiment with the idea of applying the KLEMS methodology to labor inputs, letting the educational level of the employees be the counterpart of different types of capital. In this way, we arrive at two labor input series of our own, which we shall contrast with other available labor input series. We shall use the compared series as inputs in the model that we chose in Section 2.3, i.e. AR(1) model which corresponds to (19) with $\tau = 1$, and we shall use log likelihood as the criterion of success of the various input series combinations.

2.6.1 Constructing measures of capital input

The capital input series that we construct correspond to two different classifications of capital goods. The first and simpler one (below referred to as Investment classification (2)) classifies quarterly capital formation into investment in intellectual property products (plus cultivated biological resources due to data limitations) and other investment. The second

6 See Timmer et al. (2007). Statistics Finland has provided a brief yet rigorous overview of the methodology in Tilastokeskus (2017) .

Figure 2.5 Capital input series, index 1990q1 = 100



classification (Investment classification (6)) includes six categories. These have been obtained by dividing the “other investment” category into five further classes. These are investment in residential buildings; in non-residential buildings; in other construction and land improvements; in machinery, equipment and weapons systems; and in transport equipment.

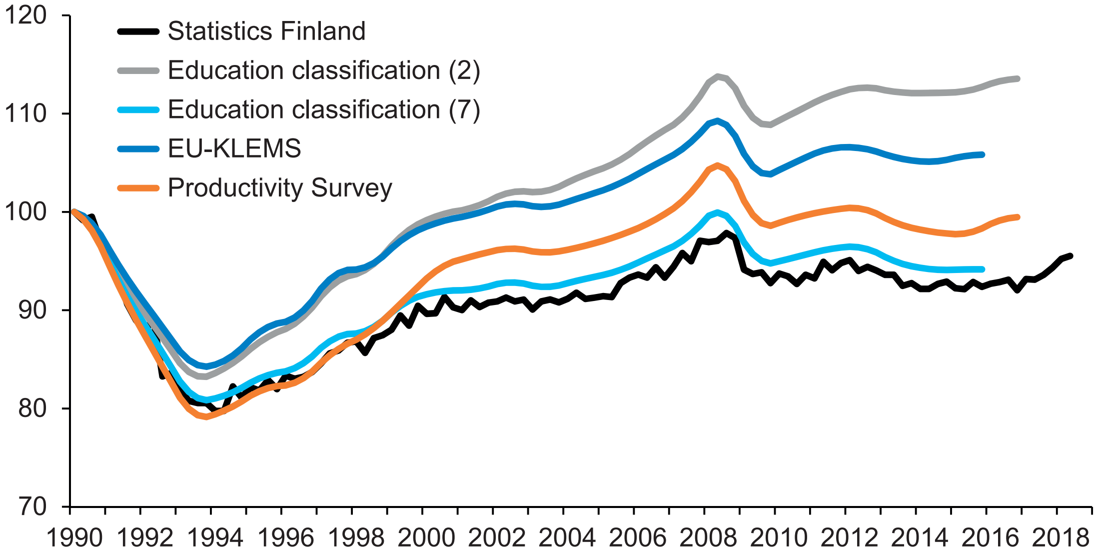
To be able to apply the KLEMS methodology, however, we need estimates of average rental rates as well as a depreciation rate for each capital good category. For these, we use the estimated rates from the Productivity Survey provided by Statistics Finland. For the latest quarters the rental rates might not be available, and for these quarters we assume that the rental structure stays the same as it was in the last available data point. Note that an important assumption behind the KLEMS methodology is that the differences in rental rates between the capital goods categories mirror differences in their productivity. Hence, substitution of low rental rate capital goods by higher rental rate capital goods would reflect substitution towards capital goods with higher productivity.

In Figure 2.5, the constructed capital input series (noted as Investment classification (2) and (6)) are depicted together with three other capital input series. The one named as Statistics Finland is the baseline case as it is just the interpolated yearly net capital stock series from the national accounts. We also have included two other series that follow the KLEMS methodology, the capital input series from the Productivity Survey and from the EU-KLEMS project. These are yearly series which we have interpolated to quarters using the Denton-Cholette method with a constant indicator series.

2.6.2 Constructing measures of labor input

We also construct two labor input series, which correspond to different educational classifications. The first one follows the classification of the working age population into people with a tertiary qualification and people without one (Education classification (2)). The other one (Education classification (7)) has seven categories: basic education, secondary education or post-secondary non-tertiary education, short-cycle tertiary education, Bachelor’s or equivalent, Master’s or equivalent, Doctoral or equivalent, and other. In constructing the labor input

Figure 2.6 Labor input series, index 1990q1 = 100



series, we follow the same KLEMS methodology as with the capital input series. In addition to assuming that the average private sector wages of the educational categories reflect their productivity, due to data limitations we have to assume that the educational classification of the working age population is a good proxy for the educational structure of the working hours.

Unfortunately, data on the average wages by educational category are not readily available prior to 2006. We extrapolate the wage structure to 1990 by using an estimated log-linear relationship between the share of the wage sum of an education category and its share in the working age population.

In Figure 2.6 above, the constructed labor input series are depicted with three other labor input series. As before, the series named “Statistics Finland” is the baseline case from the national accounts. We also consider the labor input series from the Productivity Survey and from the EU-KLEMS project. Both the Productivity Survey and the EU-KLEMS project consider three educational categories, three age categories, and two gender categories. In addition to these demographic variables the Productivity Survey uses 63 industries in determining the labor input, whereas the EU-KLEMS project has 19. Hence, they have 1 134 and 342 categories respectively. Again, this very fine split places strong demands on data, with the result that the series are updated with a long lag.

2.6.3 Comparing input series combinations

Table 2.2 contains the results from estimations of the empirical model we chose in section Section 2.3 (i.e. the AR(1) model which corresponds to (19) with $\tau = 1$) when the input series consist of various combinations of the capital and labor input series we introduced in subsections 2.6.1 and 2.6.2. (Note that in Table 2.2 the capital input series correspond to columns and the labor input series correspond to rows.) The idea which underlies our comparisons is that if an input series which tries to take some productivity changes into account within itself succeeds in its goal, it should leave less variation of the data unaccounted for in the estimation. This should show up as a larger log likelihood.

Table 2.2 Log-likelihoods for input series combinations

Capital input	Statistics Finland	EU-KLEMS	Productivity Survey	Investment classification (6)	Investment Classification (2)
Labor Input					
Statistics Finland	-43.17	-42.44	-42.24	-42.60	-42.71
EU-KLEMS	-44.12	-43.94	-43.35	-43.97	-44.15
Productivity Survey	-44.04	-43.86	-43.36	-43.82	-44.01
Education classification (2)	-44.14	-44.12	-43.87	-44.11	-44.08
Education classification (7)	-43.43	-42.69	-42.48	-42.88	-42.98

The estimation period is 1990Q2–2015Q4 because of data limitations (which are partly due to the large lag in the publication of EU-KLEMS and Statistics Finland productivity survey data). As it can be seen from the table, the largest log likelihood is arrived at with the combination of the Productivity Survey capital series and the plain Statistics Finland national accounts labor hours. It is also noteworthy that these two series dominate their counterparts in all combinations. I.e., in combination with any given capital input series, plain labor hours lead to the largest log likelihood, and similarly for the Productivity Survey capital input. However, one should also note that the differences in log likelihood seem minor.

Interestingly, our series Investment classification (6) performs decently, even though the classification is much more coarse grained than the ones used by the productivity survey and the EU-KLEMS project. It has also the advantage of being up to date with the quarterly national accounts' releases. In summary, taking account productivity developments in the capital input series seems to provide additional value to the estimation, even though the differences are fairly small.

However, somewhat surprisingly, this appears not to be the case with the labor input series. The failure of the more elaborate labor input series to yield (when measured by log likelihood) "better" productivity series might be due to slow adaptation of wages to changes in productivity, or to large internal variations in the productivity of the considered labor input types. In the case of the labor input series that we have constructed ourselves (labor classification (2) and (7)), the extrapolations that we made because of data limitations might also have contributed to the negative result.

2.7 The trend and cycle components of the productivity series

As we explained in the introductory section 2.2, the commission production function methodology for estimating the output gap is based on a Cobb-Douglas production function of the form (1), i.e.

$$Y = AL^{\alpha}K^{1-\alpha}$$

The observed total factor productivity A_t can according to the commission methodology be divided into a cyclical component C_t and trend component P_t so that

$$A_t = P_t C_t$$

and – according to the model which motivates Commission's method – the cyclical component can be expressed in the form

$$C = U_L^{\alpha} U_K^{1-\alpha}$$

where U_L and U_K measure the degree of utilization of labor and capital (Havik et al., 2014, p. 32).

However, the Commission's production function methodology does not provide tools for assessing separately the extents to which the utilization of labor and of capital varies during the business cycle. Rather, the method assumes – letting lowercase letters denote the logarithms of the quantities which are represented by the corresponding capital letters – that

(25) $$u_L = \gamma u_K + \varepsilon$$

where $\gamma > 0$ and ε is a random shock (ibid.).

Commission's method does not provide tools for estimating γ but only for estimating the trend and cycle components P_t and C_t. They are estimated using a Kalman filter with the model parameters estimated in a Bayesian framework, and a capacity utilization indicator is used as a signal variable for the cyclical component of TFP. This makes sense if the indicator provides information on the utilization of both labor and capital. However, if this is the case, it should be possible to apply the same decomposition procedure not only to the Cobb-Douglas TFP, but also separately to the labor augmenting and to the capital augmenting productivity series that we have constructed.

The Kalman filter model of the Commission contains the logarithm $tfp_t = \ln A_t$ of total factor productivity and a capacity utilization indicator (CUBS, below denoted by u_t) as its signals. The state variables are the logarithm of the trend component ($p_t = \ln P_t$) and of the cyclical component ($c_t = \ln C_t$), as well as a new variable μ_t. Their dynamics is given by[7]

(26) $$\begin{cases} \Delta p_t = \mu_{t-1} \\ \mu_t = \omega\left(1-\rho_{EC}\right) + \rho_{EC}\mu_{t-1} + a_{\mu t} \\ c_t = 2A\cos\left(2\pi/\tau_{EC}\right)c_{t-1} - A^2 c_{t-2} + a_{ct} \end{cases}$$

7 We have slightly modified the notation used by Havik et al. (2014, p. 59), in order to avoid confusion with the symbols that we have introduced previously.

where ω, ρ_{EC}, A_{EC}, and τ_{EC} are parameters and $a_{\mu t}$ and a_{ct} are error distributions. The two signals relate to the unobservable state variables via

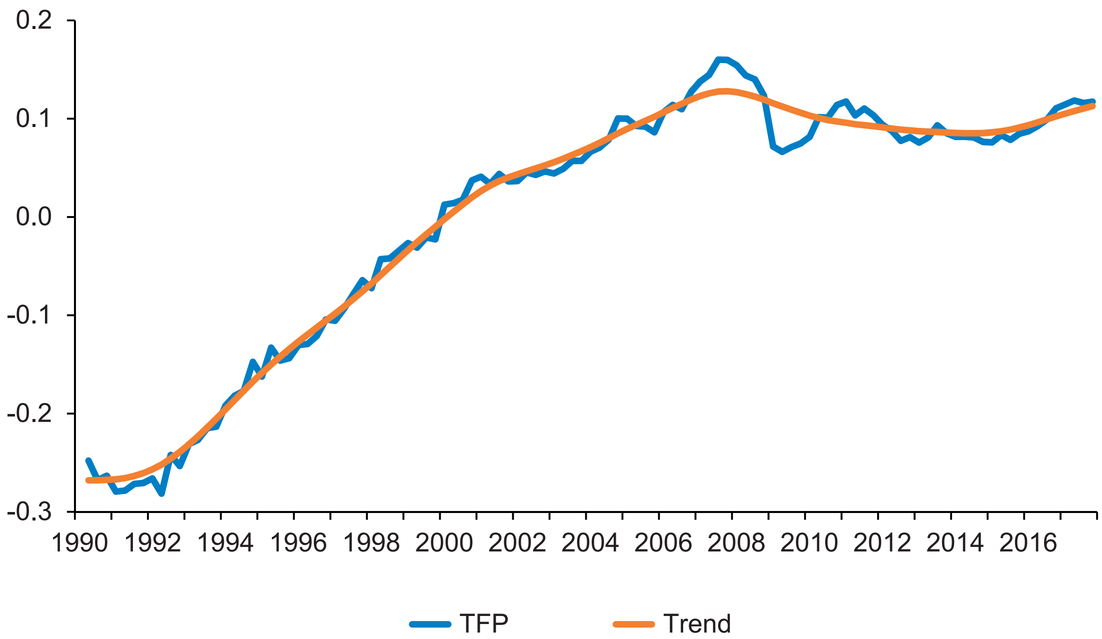
$$(27) \qquad \begin{cases} tfp_t = p_t + c_t \\ u_t = \mu_U + \beta c_t + e_{Ut} \\ e_{Ut} = \delta_U e_{t-1} + a_{Ut} \end{cases}$$

where μ_U, β, and δ_U are parameters and e_{Ut} and a_{Ut} are error terms.[8]

It is natural to ask whether a shift from the Cobb-Douglas function to a CES function would change the results that this method yields. We have addressed this question by applying the Commission's methodology to the CES function productivity series that we estimated in Section 2.5. More specifically, we think of the labor augmenting productivity $\ln B_t / \bar{B}$ (given by (21)) and the capital augmenting productivity $\ln X_t / \bar{X}$ (given by (22)) as observables, with which we have replaced tfp_t (i.e. the total factor productivity of the Cobb-Douglas function) in (27). In other words, we have viewed the capacity utilization measure as a log-linear function of the cyclical component of each of the two productivity series, plus error terms.

In Figure 2.7, the logarithm of the Cobb-Douglas total factor productivity is shown together with its estimated trend component, which has been estimated using the Commission's methodology with the spring 2018 prior values for Finland. However, we have switched from annual data, which is actually used by the Commission, to quarterly data in order to improve comparability with the results from our CES model. The European Commission uses GDP as the measure of output while distinguishing the trend and cyclical components of TFP, and since we have used value added as the measure of output, we have switched to using value added also in the Commission's method.

Figure 2.7 Cobb-Douglas TFP and it's trend, log levels



8 See Havik et al. (2014, pp. 59–60), which also presents the (rather elaborate) prior distributions of the parameters and the variances of the error terms.

We applied the same procedure and priors to the labor and capital augmenting productivity series, using the AR(1)-specification and plain national accounts input data. These series and their trend estimates are depicted in Figures 2.8 and 2.9. Figure 2.8 and 2.9 illustrate the point, already made in Section 2.5, that cyclical factors seem to affect capital augmenting productivity much more strongly than labor augmenting productivity. Figure 2.9 suggests that the business cycle has only a minor effect on labor augmenting productivity, which seems to fluctuate around its trend in a more or less random fashion. This also suggests that the theoretical parameter γ, which appears in the Commission's model (see equation (25)) but which remains unidentified in the model, would actually be close to zero.

Figure 2.8 Capital augmenting technical progress and it's trend, log levels

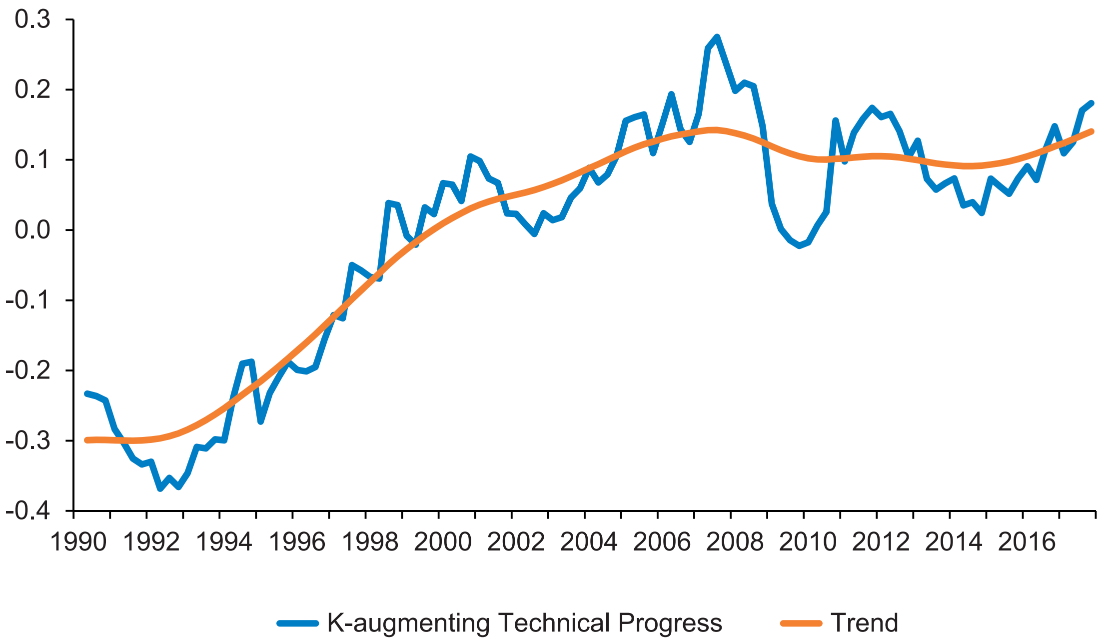
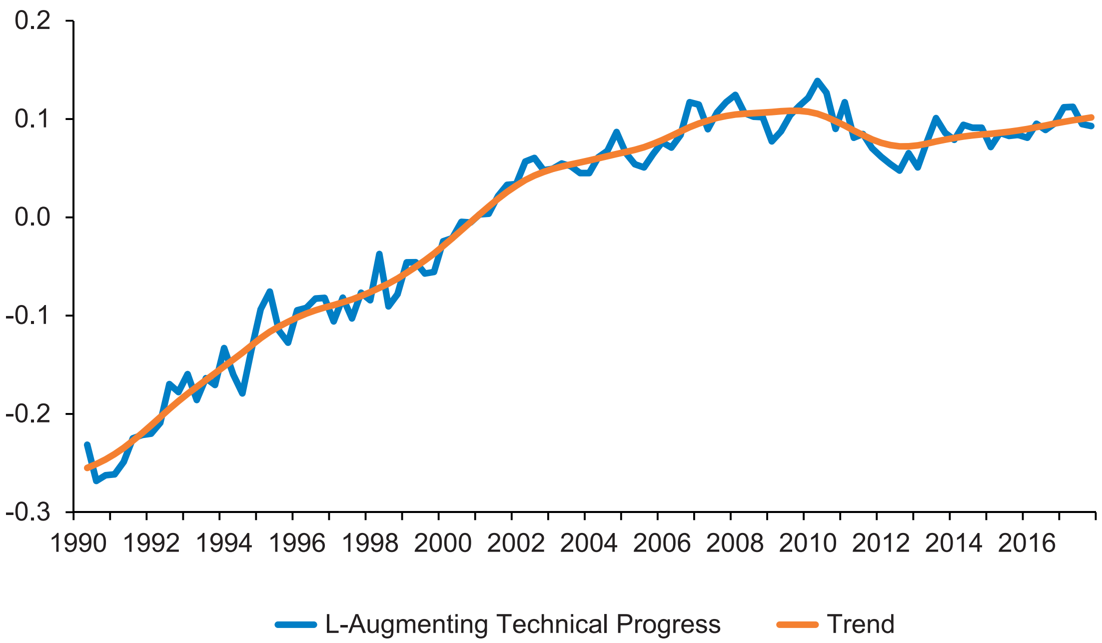


Figure 2.9 Labor augmenting technical progress and it's trend, log levels



The large procyclicality of the capital augmenting series is easy to understand intuitively. After all, the capital series is a measure of the net capital stock and does not separate the capital goods that are in full use from those that are not, and the swings in the utilization of capital should also be noticeable as swings in the capital augmenting series. The lack of procyclicality (or even a slight countercyclicality, as Figure 2.4 suggests) of the labor augmenting series is more puzzling, and there are a variety of explanations that one could suggest for it. The most obvious explanation is that during downturns there are layoffs which reduce the labor input. In addition, it might also be the case that labor hours are cut more from less productive workers than the ones with higher productivity. Another possible source of countercyclicality is that employed workers react to downturns by increasing their effort: the more there is competition for the same jobs, the more workers may have incentives to demonstrate their contribution to the employers. These countercyclical forces would then have to be more pronounced than the procyclical forces such as labor-hoarding in order to produce the displayed pattern.

2.8 Comparing output gaps in the Cobb-Douglas and CES specifications

In European Commission's methodology, *potential output* differs from the actual output both because it corresponds to the "potential" (i.e. equilibrium) labor input rather than the actual labor input, and because it corresponds to the trend (rather than to both trend and cycle) component of the total factor productivity. In other words, potential output is given by (cf. Havik et al. (2014), p. 12)

$$(28) \qquad Y_t^{POT,CD} = P_t \left(L_t^{POT} \right)^{\alpha} K_t^{1-\alpha}$$

when L_t^{POT} is the equilibrium labor input. Given a potential output Y_t^{POT}, the output gap can be defined as

$$(29) \qquad OG_t = \frac{Y_t - Y_t^{POT}}{Y_t^{POT}}$$

Commission's method, which is based on the Kalman filter (26)-(27), leads to an estimate $P_t = \exp(p_t)$ of the trend of the total factor productivity, which can be plugged into (28) to produce an estimate of the potential output. We have used the same Kalman filter for estimating the trends of $\ln\left(B_t / \widetilde{B}\right)$ and $\ln\left(X_t / \widetilde{X}\right)$. Calling these estimates (say) $b_{p,t}$ and $x_{p,t}$, we may define our estimate of the potential output, calculated on the basis of our CES function (13), as

$$(30) \qquad Y_{POTCES,t} = \overline{Y} \left[\overline{\pi} \left(\exp\left(x_{P,t}\right) \frac{K_t}{\overline{K}} \right)^{-\rho} + (\zeta^{-\rho} - \overline{\pi}) \left(\exp\left(b_{P,t}\right) \frac{L_{POT}}{\overline{L}} \right)^{-\rho} \right]^{-\frac{1}{\rho}}$$

Our two estimates of potential output $Y_{POTCD,t}$ and $Y_{POTCES,t}$ can now be used for calculating output gap estimates in accordance with (29).

Figure 2.10 shows, in addition to the actual output of the economy, the potential output which corresponds to Commission's model with a Cobb-Douglas specification and the potential output which corresponds to our CES model with the AR(1)-specification and plain national accounts input data. The two potential output estimates seem almost identical in

Figure 2.10, but the difference between the two approaches becomes more marked when output gaps are considered. They are shown in Figure 2.11.

As Figure 2.11 shows, CES function leads, in general, to output gaps which are larger in absolute value (i.e., larger in booms and more negative in recessions). This means that when the CES production function is chosen, the calculated potential output is smaller in booms and larger in recessions. In other words, the potential output estimates to which the CES

Figure 2.10 Potential outputs vs. output

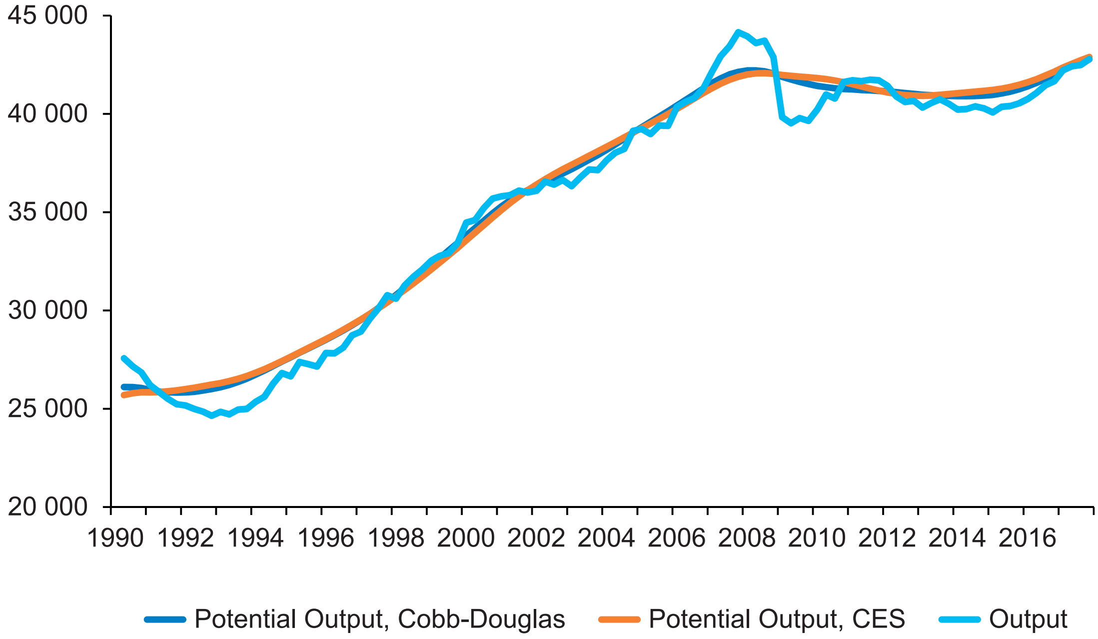


Figure 2.11 Output gap estimates for Cobb-Douglas and CES

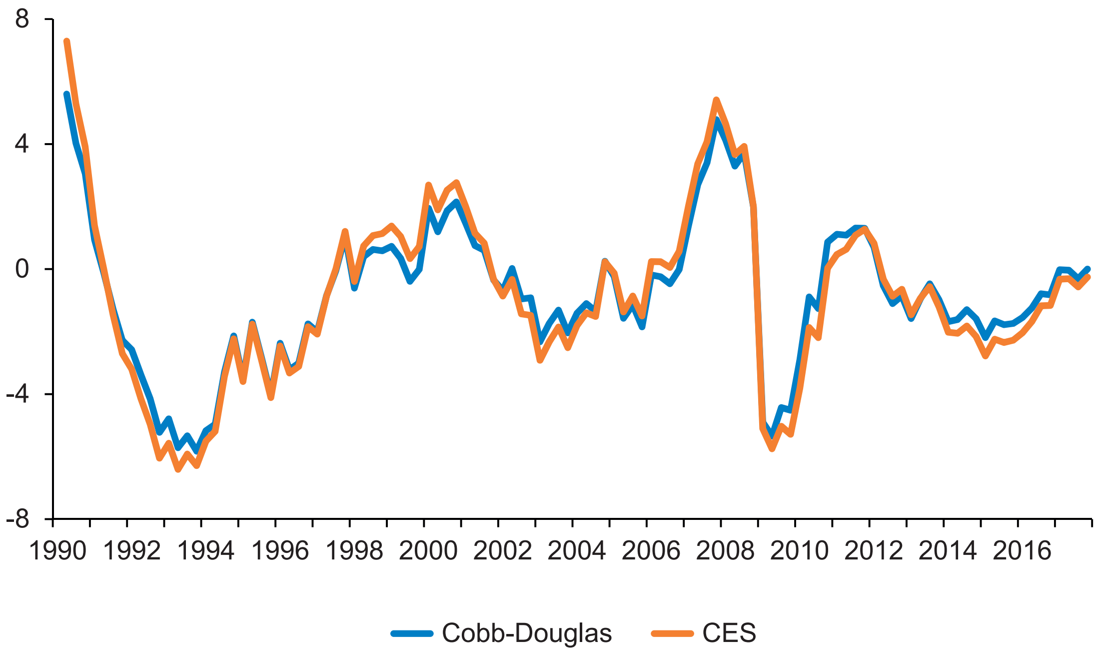
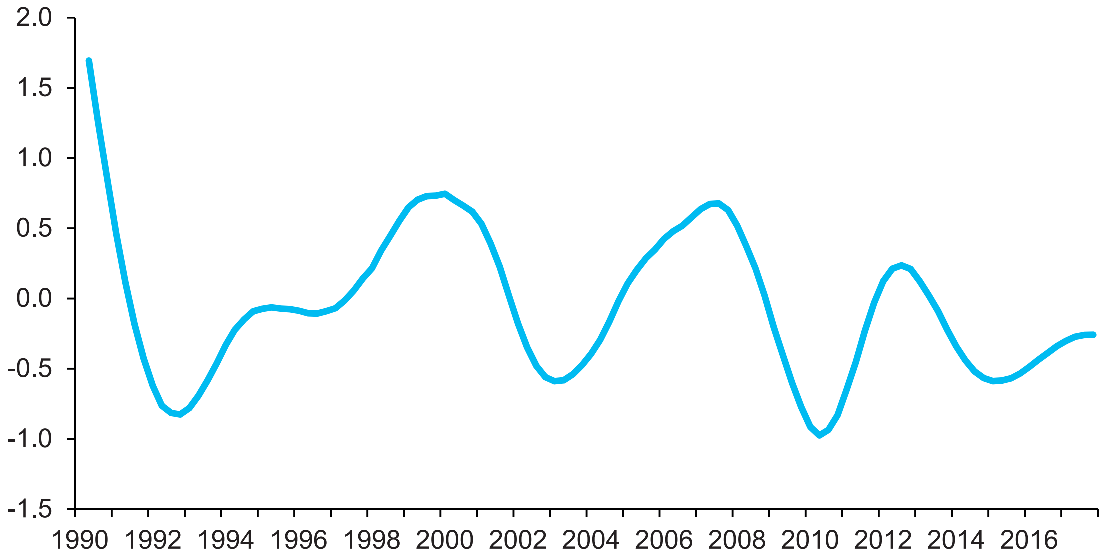


Figure 2.12 Difference (in percentage points) between Cobb-Douglas and CES output gap estimates



function leads are more stable and less prone to be affected by the business cycle. Taking the difference of the two output gap series, depicted in Figure 2.12, we can easily note that the differences between these two estimates have been substantial: during the financial crisis for example, the CES-based output gaps are around one percentage point lower (i.e. more negative) than the Cobb-Douglas ones in the case with the Statistics Finland national accounts inputs.

In section 2.7 we concluded that one of the capital input series that we constructed – the one we labeled investment classification (6) – was preferable to the national accounts net capital stock series. It has turned out that when we estimate the output gap with this specification, the differences between the CES and Cobb-Douglas based output gaps are further widened.

3 ESTIMATION OF THE POTENTIAL OUTPUT BY USING THE SEQUENTIAL MONTE CARLO

Tero Kuusi and Markku Lehmus

3.1 Introduction

In this section we introduce novel methods to estimation of the potential output and apply them to analyze the production potential of the Finnish economy. Our starting point is the standard definition of the potential as the level of output that an economy can produce without triggering above-normal inflation. The definition is originally introduced by Okun who emphasized that potential output is a “supply side concept, a measure of productive capacity.” (Coibion et al., forthcoming). The fundamental problem in using the potential output as a policy tool, is that it is unobservable. Rather, its measurement requires assessments on several quantities that are difficult to measure, and hence these must be estimated.

Our analysis addresses a few problematic fields in the estimation of the potential output by means of the production function assessment. We revisit the task of estimating the NAWRU – the task that is theoretically well-based but empirically very difficult to tackle. The methodology of the EC has lately become criticized by some economists (see for instance Fioramanti & Waldmann, 2016) for example because the economic downturns do not show up clearly in inflation, and therefore the inflation-neutral unemployment is not easily inferred from the data. Another important example is the estimation of the potential total-factor productivity, TFP. While TFP captures the effects of changes in technology and other productivity shocks that have been major determinants of the recent business cycles, the problem is that the variable is like a black box comprising all the potential productivity enhancements achieved in the economy, including also measurement errors. This gives little insights how to separate between different sources of productivity growth.

In addition, there is a considerable amount of ambiguity in how smooth the potential estimates should be. For example, the U.S. government’s estimates of NAIRU are based on a rather structural idea of an equilibrium unemployment rate as compared to the European Commission, and consequently, NAIRU estimates for the US are typically considerably less volatile than those for the euro area countries. The smoothness of the potential is typically determined with the signal-to-noise ratio parameter captured from the variances of the shock terms of the trend and cyclical shocks The larger the ratio, the more volatile the potential is. To identify the cycle, the estimations typically involve restrictions. The restrictions may be needed so that the cycle is a stationary process, while the potential is non-stationary, thus reflecting permanent changes in the variable in question. However, the smoothness assumptions are not without problems. They may, for example, impose mechanical rules on how fast the cyclical shocks die out, and therefore the cyclical component may be over- or underestimated during the business cycle, and the estimates of potential may not correctly represent the supply side. Rather, in contradiction to their definition, the estimates of potential output are often correlated with underlying cyclical economic shocks. (Coibion et al., forthcoming).

3.2 The current assessment of the potential and its validity criteria

In what follows, we assess the Finnish potential output by using a novel Bayesian estimation approach, i.e. the Sequential Monte Carlo (SMC). We describe it in the methodology Box 3.1 and in the Appendix of this section.

In terms of assessing how well our models perform, we acknowledge that there is a considerable number of assessment criteria available. The first and most natural is the statistical credibility of the model: the credibility with which a specific model describes a phenomenon, beginning with the selected structure. From the standpoint of statistical credibility, the maximum likelihood (ML) estimates conducted for the model are important. While we use prior information concerning the time-series properties of the business cycle, we aim at making sure that they do not drive our results.

In addition, assessment of credibility also requires analyses over different time periods. Because the output gap is often used as a real-time indicator of economic policy, the behavior at the endpoints of the data should be an important determinant of the indicator's usefulness in the policy analysis.

Although the model may seem credible from the statistical perspective, its use may not always be justifiable from a theoretical standpoint. For example, the variation of the cycle should be strongly correlated with inflation and the output gaps should be stationary by definition. Moreover, the cyclical component should be strongly correlated with other key determinants of the business cycle, such as the capacity utilization of the business capital and the financial factors.

Furthermore, credibility can be assessed in relation to data outside the model, for example in the case of data from the labor market and from key sectors in terms of technological development. If the theory or external observations are clearly incompatible with the statistical model used, this probably means that the statistical model has been prepared incorrectly and should be altered.

In our analysis, we aim to strike a balance between the alternative viewpoints. We use an extended multivariate filter to isolate the latent part of the economic growth that is expected to be caused by permanent shocks. By extending the traditional models used, for example, by the European Commission, we aim at a better judgement of the feasibility of our estimates. We utilize the cross-variation of different components of the production function, various indicators of the business cycle, as well as detailed Phillips curve specifications.

3.3 Estimation of the labor force variables

We first apply the SMC method to investigate the potential level of the labor input. While we use the Phillips curve to identify the non-accelerating inflation rate of unemployment, we simultaneously model the cross-variation of the cyclical components of unemployment and the labor force participation rate, as well as other cyclical factors to jointly identify the business cycle. In this subsection we first introduce the key challenges in the estimation and then outline our model.

Box 3.1 The calculation of the potential by using the Sequential Monte Carlo

Assessment of potential output is carried out using a Bayesian method of calculation, which means that the final selection of a model is based not only on the distribution of likelihood generated by the data, but also on the preset probabilities of parameter values (prior probability distributions). These a priori beliefs can be based on economic theory or previous empirical research. Prior probability distributions enable the re-weighing of maximum likelihood estimates, leading to a final understanding of the expected values of the parameters (posterior probability distribution).

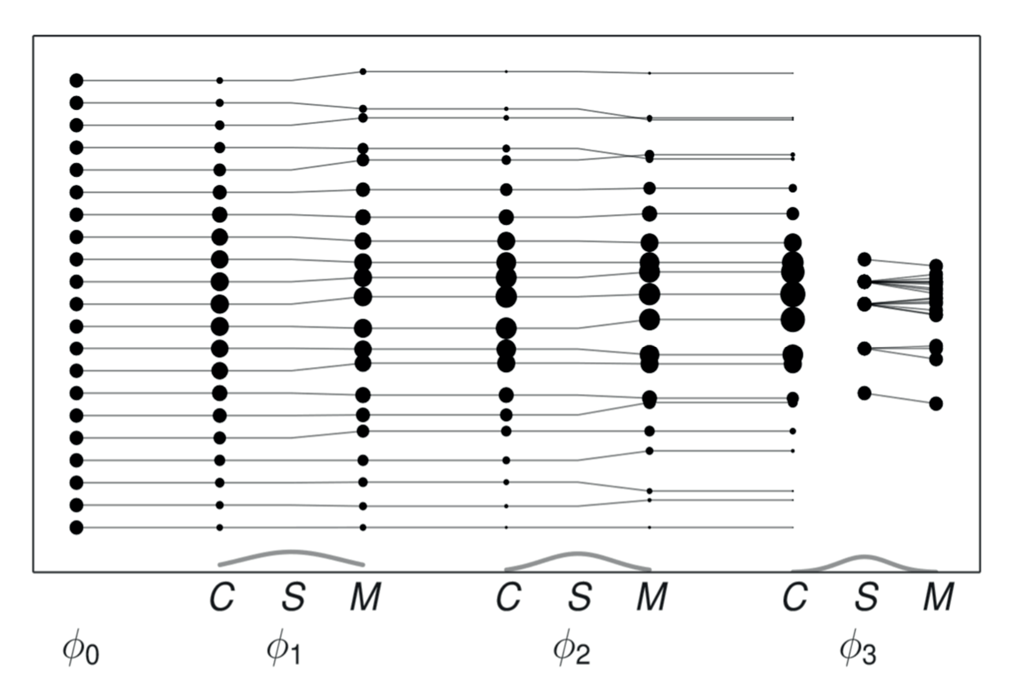
Unlike the maximum likelihood method, the posterior probability distribution used in the model does not include a closed form solution. There are several possible approaches to the measurement of the posterior distribution. The traditional way is to use the Markov Chain Monte Carlo method (MCMC), whereby parameter values are drawn from a proposal distribution in order to simulate a posterior distribution via a so-called Gibbs sampling. The main idea is to create a sequence of serially correlated draws such that the distribution of the parameters converges to the posterior distribution. For a more detailed description of this method and its use in the assessment of the potential output in the European policy context, see Planas & Rossi (2014) and Havik et al. (2014).

The recent macroeconometric literature suggests that the standard approach is not without problems especially when the dimensionality of the estimated parameter vector is large. A key reason is that in the typical models the disentangling of internal versus external propagation mechanisms can be difficult. The probability distribution of the model is often irregular and has multimodal posteriors, i.e. the estimation does not necessary converge to the local optimum, or there are several local optimums with alternative parameterizations that have similar likelihoods (Herbst & Schorfheide, 2016).

We can expect that our models suffer from similar problems. In particular, the estimation of the NAWRU provides notorious examples of the difficulty to isolate the external shocks and the influence of the business cycle on the labor market. The simultaneous movement of unemployment and inflation can be both a sign of wage moderation and an exogenous shock to the fundaments of the economy, such as technology. Similarly, changes in the total-factor productivity can be either due to adjustment of the used capacity by the firms, or technological changes that have more long-term effects. The resulting ambiguity makes it difficult to determine the relative importance of alternative shocks, and thus the state of the economy, and ultimately the economic projections and policy recommendations. (see, e.g., Kuusi, 2017; 2018).

To overcome these methodological concerns, we use a novel approach to the estimation of the potential output. In particular, we use the Sequential Monte Carlo (SMC) method that is better suited for the analysis of irregular and multimodal posterior distributions. The recent literature suggests that the SMC metodology can improve the performance of the estimation of large-scale, latent-variable models. In particular, Herbst and Schorfheide (2014) show illustrations consisting of the well-known Smets and Wouters (2003) model and a larger, so called, news shock model (see, e.g., Beaudry & Portier, 2007). They show that the SMC algorithm is better suited for multimodal and irregular posterior distributions than the widely used random walk Metropolis–Hastings algorithm. They find that a more diffuse prior for the Smets and Wouters model improves its marginal data density and that a slight modification of the prior may lead to drastic changes in the posterior inference about the functioning of the model. Further examples of the use of SMC in the DSGE context are provided by Herbst and Schorfheide (2016). In case of the estimation Markov switching models, Bognanni and Herbst (2018) argue that SMC has the advantages of generality, parallelizability, and freedom from reliance on particular

Figure 3.1 The dynamics of the SMC algorithm



Source: Herbst & Schorfheide (2016).

analytical relationships between prior and likelihood. Surveys on the methodology are provided by Creal (2012) and Herbst & Schorfheide (2016).

To our knowledge, this is the first attempt to use SMC to assess the potential output*. While we leave the more detailed description of the SMC method to the Appendix, an outline of the methodology is provided next with an illustrated example. Let us consider a parameter, θ, that is estimated with the methodology.

To characterize the posterior probability distribution, the method resorts to the notion of particles. A particle i is a pair of a parameter value and its probability (θ^i,p^i). The probability distribution is characterized by a large number (N) of particles. The idea of the SMC is to iteratively adjust the positions and probabilities of the individual particles in order to ultimately correctly specify the posterior distribution of the parameter. The iterative process is started with an initial guess for the distribution, denoted in Figure 3.1 θ_0 by that is based on the information concerning the prior distribution. In each round of the iteration, steps are taken to use the previous guess as a basis of a new, improved guess about the posterior distribution. More weight is gradually given on the approximated posterior density. Ultimately, under certain conditions, the approximation converges to the actual posterior density by the last iteration that we denote by θ_M.

During each round of the iteration, the characteristics of the particles are updated in three steps. The first step adjusts the weights of the particles, the second step resamples the particles, and the third step propagates the obtained particles via a Markov Chain Monte Carlo algorithm.

* We thank the organizers of the 3rd PIER Workshop on Quantitative Tools for Macroeconomic Policy Analysis in 2017 at the University of Pennsylvania for kindly sharing the algorithms that were used in the estimations.

Before going further, we make a notational remark. We denote the aggregate labor input in working hours L_t^{pot}. It can be decomposed as follows: First, the potential workforce is adjusted based on the level of structural unemployment, $NAWRU_t$. Potential workforce is, furthermore, the product of the number of population of working age POP_t^W, average level of participation $PART_t^{pot}$ and working hours per employee H_t^{pot}:

$$L_t^{pot} = POP_t^W PART_t^{pot}(1 - NAWRU_t)H_t^{pot}$$

3.3.1 NAWRU and the measurement of the unemployment gap with the Phillips curve

A key task in measuring the potential output is the separation of a cyclical component of the unemployment from the structural component. The structural unemployment rate in turn is typically analyzed using the concept of the non-accelerating inflation rate of unemployment NAIRU, or non-accelerating wage inflation rate of unemployment NAWRU, the former referring to the relationship between inflation and unemployment and the latter to the relationship between wage inflation and unemployment.

The idea of NAWRU can be traced back to Phillips (1958) who observed that there was a stable empirical relationship between wage inflation and the unemployment rate in the UK. The traditional Phillips curve also suggested that the systematic negative relationship between wage inflation and the unemployment rate could be exploited by policy-makers while they could choose between either accepting high inflation with low unemployment rate, or conversely, they could benefit from low inflation but this would come with cost of a higher unemployment rate. Implicitly, the trade-off was based on the assumption of constant inflation expectations.

The traditional Phillips curve was challenged in the 1970s when inflation and unemployment started to increase simultaneously. This phenomenon, known as ”stagflation” turned the economists’ focus on inflation expectations: the wage settlers would not probably assume that inflation expectations are constant, but instead, the expectations could change when the realized inflation numbers or some other relevant information about the economy would change. Hence in the literature, traditional Phillips was followed by an accelerationist Phillips curve (also known as expectations-augmented Phillips curve) where it was the change in wage inflation that was related to the unemployment gap.

In our estimation of the NAWRU, we take stock on the European Commission’s estimation method. In their estimation of NAWRU rates, the European commission aims at distinguishing cyclical from structural changes in unemployment (Havik et al., 2014). The idea behind the method is that if wage inflation clearly reacts to growth in cyclical unemployment, the observed connection can be turned around, and the cyclical unemployment growth can, for its part, be effectively determined based on inflation.

The Commission uses a general labor market framework whose features are ultimately estimated based on the data and correspond to the predictions of various labor market theories (see Havik et al., 2014). Outside the long-term equilibrium, the short-term state of the labor market can be assessed using the Phillips curve. In the follows, we omit a thorough theoretical derivations of the Phillips curve. Rather, we refer to the of publications by Havik et al.

(2014) and Planas & Rossi (2014). It is sufficient to note that the NAWRU refers to a labor-market equilibrium. Outside the equilibrium, the short-term state of the labor market can be assessed using the so-called neo-Keynesian Phillips curve. The curve is derived from a dynamic general equilibrium model[9] whereby a randomly chosen proportion of employees may re-negotiate their wage during the year, whereas the rest of the wages (whose agreement term is still ongoing) are expected to develop according to retrospective index adjustments. There is a connection between negotiated salaries and employment: increasing unemployment is associated with lower wage offers. Indexed wages, on the other hand, follow the development of real unit labor costs. Expectations related to the inflation and output gap are unbiased. It is assumed that unemployment will follow the second order autoregressive process, as in the United States, on an annual frequency, the relation can be written out as an empirically testable equation as follows where t refers to quarters:

$$(1) \qquad RULC_t = \alpha + \gamma RULC_{t-1} + \psi_0(u_t - u_t^*) + \psi_1(u_{t-4} - u_{t-4}^*) + e_t,$$

where $RULC_t$ is the rate of change of real unit labor costs, $u_t - u_t^*$ is the cyclical component of unemployment and α is a term that includes various long-term relations (such as the average rate of increase in productivity).

The following relations apply to the variables of the equation: $\psi_0 < 0$ means that real unit labor costs can be expected to decrease when unemployment is at a high level. The magnitude of the parameter depends on the length of the agreement terms: if the terms are long, wage inflation is only slightly dependent on unemployment. On the other hand, if unemployment is highly path-dependent, ψ_0 is large, which implies that the wage level has already adjusted to unemployment. Due to self-correcting forces in the economy, i.e. recovery of the wages from the temporary deviation, ψ_1 can be expected to be positive. In equation (1), γ indicates the weight attributed to the index variable in the agreement negotiations (development of the unit labor costs of the previous year) compared to the long-term development of wages, which remains part of the constant term α within the equation. Strong indexing generates greater autocorrelation within the wage inflation variable.

3.3.2 Taking stock of the recent NAWRU critique

The task of estimating the NAWRU is theoretically well-based but empirically very difficult. The methodology has lately become criticised by some economists (see for instance Fioramanti & Waldmann, 2016). Yet another issue relating to NAWRU and the Phillips curve is the recent observation that the relationship between unemployment and wage growth is somewhat broken. For instance, Haldane (2017) states that the Phillips curve relationship has been anything but strong and stable in the UK, and that same flatness in the Phillips curve can be observed in a number of other countries as well. The behaviour of inflation does not necessarily correspond to the Neo-Keynesian Phillips curve, even though it includes a delayed inflation term. For example, Stock and Watson (2010) are of the opinion that, in the US, an increase in unemployment does decrease inflation, but this effect wears off when a higher level of unemployment has lasted for 11 quarters.

One of the underlying causes of this could be anchored inflation expectations, whose effects during the euro crisis are a topic of discussion, see for example Krugman (2013). Downward wage rigidities (for example, pressure not to reduce nominal wages) can affect the

9 For more details, see Gali (2011).

relation between inflation and unemployment in such a way that it does not correspond to the Neo-Keynesian Phillips curve. (Daly & Hobijn, 2013). In Finland's case, there is clear evidence of fairly substantial wage inelasticity in the crisis of the early 1990s (Gorodnichenko et al., 2012).

In order to analyze the implications of alternative ways to introduce the inflation expectations, we resort to two additional approaches. In our baseline estimation, we add an additional term that controls for the observed expectations:

$$(2) \qquad RULC_t = \alpha + \gamma_f E[RULC_{t+4}] + \gamma RULC_{t-1} + \psi_0(u_t - u_t^*) + \psi_1(u_{t-4} - u_{t-4}^*) + e_t,$$

As an alternative, we introduce anchored inflation expectations similarly to Rusticelli et al. (2015). They fix the constant term of the Phillips curve to introduce the level of anchored expectations. Furthermore, we introduce an additional lagged inflation term to the equation in order to match their specification:

$$(3) \qquad RULC_t = \bar{\alpha} + \gamma_1 RULC_{t-4} + \gamma_2 RULC_{t-8} + \psi_0(u_t - u_t^*) + \psi_1(u_{t-4} - u_{t-4}^*) + e_t,$$

In addition to the specification of the Phillips curve, there is considerable amount of ambiguity in how smooth the NAIRU estimates should be. For example, the U.S. government's estimates of NAIRU are based on a rather structural idea of an equilibrium unemployment rate as compared to the European Commission, and consequently, NAIRU estimates for the US are typically considerably less volatile than those for the euro area countries. CBO (Congressional Budget Office), an independent US institution responsible for these calculations, rather uses the concept of "a long-term rate of unemployment", in lieu of NAIRU.

The smoothness of the NAWRU is typically determined with the signal-to-noise ratio parameter captured from the variances of the error terms of the trend and cyclical shocks The larger the ratio, the more volatile the NAWRU is, while if this parameter was zero that would imply a constant NAWRU rate. Laubach (2001), OECD (2000), and also Llaudes (2005) argue the unrestricted estimation of the signal-to-noise ratio leads easily to very flat NAIRU estimates. Ultimately, the restrictions may be needed so that the cyclical part of unemployment, the unemployment gap, is a stationary process, while the NAWRU is non-stationary, thus reflecting permanent changes in unemployment. (Hristov & Roeger, 2017).

The strong assumptions concerning the parameters of the model are not without problems. They may, for example, impose mechanical rules on how fast the cyclical shocks die out, and therefore the cyclical component may be over- or underestimated during the business cycle, and the NAWRU estimates may not correctly represent the long-term rate of unemployment. Rather, as a result of these assumptions, the estimates of potential output are often correlated with underlying economic shocks that are cyclical, and thus seem to have a strongly cyclical component. (Coibion et al., forthcoming)

In what follows, we try to find a balance between the identifying restrictions and letting the data to speak, by using a Bayesian estimation method that uses the EC parameter estimates as informative priors, but still leaving room for the estimator to adjust the parameter values.

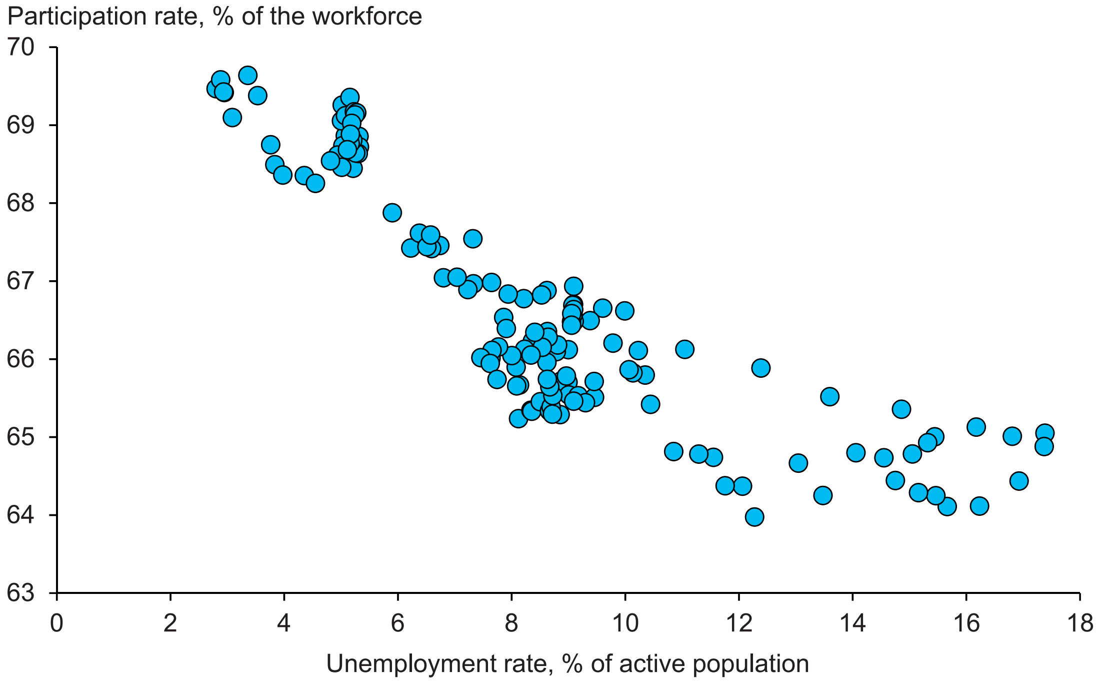
Furthermore, in order to avoid the cyclicality of our NAWRU, we provide additional information to the model about the relationship between unemployment and factors that are considered to be cyclical. Thus, our approach here is to introduce shocks to the model that are known to be strongly associated with the business cycles. In particular, we consider three alternative cyclical factors. As a standard business cycle metric, we use the manufacturing capacity utilization rate indicator. As a financial stress metric, we consider a credit spread variable that represent the spread between lending and borrowing rates. In this respect, we follow Borio et al. (2013) who argues that financial factors may be a useful tool to improve the measurement of the potential. Finally, as the Finnish economy is a small open economy with large external component in the business cycle, we also introduce the net exports. Here, we take stock on Darvas and Simon (2015). We measure the shocks in these variables as the deviation of the variable from the past 3 years average. We introduce these shocks to the model as drivers of the unobserved cyclical component of the unemployment, and use the observed sensitivity of the unemployment growth as prior information in the model.

3.3.3 Introduction of the labor force participation rate to the model

As an additional way to improve the identification of the potential labor input, we introduce a common cyclical component to the labor force participation rate and the unemployment. The labor force participation rate is a key labor market variable and has a strong link to the business cycles. We follow Barnes et al. (2013) to provide a decomposition of cyclical versus trend movements in the labor force participation rate, informed by the joint dynamics of this variable with the unemployment.

As Figure 3.2 suggests, these variables are highly correlated, and thus it is natural to suggest that such a common component indeed exists.

Figure 3.2 A scatter plot of the Finnish quarterly participation rate and the unemployment rate 1982–2017



Source: Statistics Finland and own calculations.

There are a few merits to this approach. First, we aim at improving the measurement of the potential labor force participation rate. Currently, a common approach to its estimation, for example by the European Commission, is to use the Hodrick-Prescott filter. While the filter is easy to use, it has major caveats. In addition to the imposed smoothness parameter and the participation rate time series, the filter does not include any other information to the model. As the different cyclical components of the potential labor input appear to be strongly dependent, it can be expected that their analysis together could improve the performance of the filter. Moreover, the choice of the smoothness parameter is not a straight forward one: The potential estimates are rather sensitive to its choice within a set of values that can all be considered as being feasible, as Huovari et al. (2017) has recently demonstrated with the Finnish data. Moreover, the HP filter is prone to suffer from major revisions at the endpoint of the series when new information gathers in.

Second, we expect that the information can help to identify the potential of other labor input variables. As the estimation of the NAWRU is notoriously difficult, the analysis that aims at finding a common cyclical component may also improve its evaluation. In this respect, we find that this avenue of research is open for further improvements. While our analysis focuses on the NAWRU and the participation rate, it is noticeable that the potential hours per employee, H_t^{pot} , is currently also estimated with the HP filter, and its inclusion to the model provides a natural extension to our analysis.

3.3.4 Specification of the model

In order to estimate long-term equilibrium unemployment, we build on the Commission's NAWRU methodology (Kuttner, 1994; Planas & Rossi, 2014). The method breaks unemployment down into its structural and cyclical components, of which the cyclical component has an accelerating or decelerating effect on inflation, whereas the structural component has a permanent effect on unemployment, and it is inflation-neutral.

The unemployment u_t is a sum of the trend component u_t^p and the cyclical component u_t^c so that

$$u_t = u_t^p + u_t^c.$$

The cyclical component is defined as the AR(1) model:

$$u_t^c = \phi_{c1} u_{t-1}^c + a_{ct},$$

where a_{ct} is a cyclical shock term with a variance of V_c. With regards to Finland, a trend shock is modelled with the Commission's method as a second order random walk defined by the following equations

$$u_t^p - u_{t-1}^p = \mu_{t-1} + a_{pt}$$

$$\mu_t - \mu_{t-1} = a_{\mu t}$$

In the equations, a_{pt} is a shock that affects trends directly and has a white noise distribution. Its variance is V_p. The second shock $a_{\mu t}$ affects the slope of the trend and is also white noise. Its variance is marked as V_μ.

Another equation used in the method is the Neo-Keynesian Phillips curve (Eq. 1 in the previous subsection), that can be expressed more concisely after denoting $u_t - u_t^* = u_t^c$:

$$RULC_t^w = \alpha + \gamma RULC_{t-1}^w + \psi_0 u_t^c + \psi_1 u_{t-1}^c + e_t \ ,$$

where e_t is normally distributed with variance, V_e. We use different variants of the Phillips curve, i.e. the model with the actual inflation forecasts (Eq. 2) and the model with anchored inflation expectations (Eq. 3).

In each model, we include the participation rate as an additional variable. The participation rate is decomposed to its cyclical and the trend component:

$$pr_t = pr_t^C + pr_t^p$$

The trend component is a random-walk process

$$pr_t^p = pr_{t-1}^p + e_{pt}, \ \ e_{pt} \sim \mathrm{N}(0, V_{ep})$$

where the shock process e_{pt} has a permanent effect on the participation rate. The cyclical component of the participation rate shares a common component with the cyclical unemployment. In the specification, the interaction is assumed to occur in different intervals at the dates t-1, t-4, and t-8

$$pr_t^C = \phi_{cpr0}\, u_{t-1}^C + \phi_{cpr1}\, u_{t-4}^C + \phi_{cpr2} u_{t-8}^C + \phi_{pr} pr_{t-1}^C + e_{ct}, e_{ct} \sim \mathrm{N}(0, V_{ec})$$

Furthermore, the cyclical component has a transitory AR(1) component, and its dynamics are governed by cyclical shocks e_{ct}.

Finally, we impose relationships between the business cycle factors and the cyclical component of the employment:

$$\Delta u_t^C = \beta_s * Spread_{t-4} + \beta_{cap} * capacity_t + \beta_{nexp} * nexports_t + e_{xt}, \ \ e_{xt} \sim \mathrm{N}(0, V^X)$$

The functional form of the equation is chosen based on an exploration of the unemployment and the shock variables in the data.

3.3.5 Data

We use quarterly data to estimate our model. The unemployment and participation rate series are collected from the Statistics Finland. The unemployment rate is the seasonally-adjusted ratio of unemployed persons as relative to the total active population. The participation rate is the seasonally-adjusted ratio of active population as relative to the working aged (15–74) population. The inflation variable (the real unit labor cost inflation, RULC[10]) is reported as a part of the ETLA's forecast rounds, as well as the forecasted RULCs that are available as a quarterly series of the forecasts for the following year's inflation.

Our model includes three other indicators: (1) the capacity utilization of the industrial enterprises, (2) net exports-to-GDP ratio, and (3) the interest rate spread. The capacity utilization indicator consists of estimates by industrial enterprises regarding their order books in relation to the norm, which we compiled by chaining indicator series for different time periods[11].

10 The RULC is measured by measuring the average nominal wage per hour inflation as proportional to the average productivity growth and the value-added price inflation.

11 BTEOLRSL and BTEOLL:B8S of the Confederation of Finnish Industries (EK).

The data has been available since 1976; it thus includes data on the 1990s crisis. The net exports-to-GDP ratio is measured based on the nominal exports and imports and divided by the value of the GDP. They are gathered from ETLA's database (the export and import series NKT10HT:M and NKT10HT:X). Finally, the interest rate spread variable is the spread between the household lending and borrowing rates. We use Bank of Finland's quarterly data 2003–2017, and Worldbank's annual data for the prior years that we interpolate to the quarterly frequency. The three indicator variables are measured as the deviation of the collected data from its past three years' moving average.

The data spans from the beginning of the year 1982 until the end of the year 2017.

3.4 Total-factor productivity

As a second application, we revisit the question of finding the potential level of the total-factor productivity (TFP). As TFP was already discussed in the previous parts of this report, we address its background only shortly and in those respects that are important in the current analysis.

3.4.1 Discussion of the measurement of the TFP potential

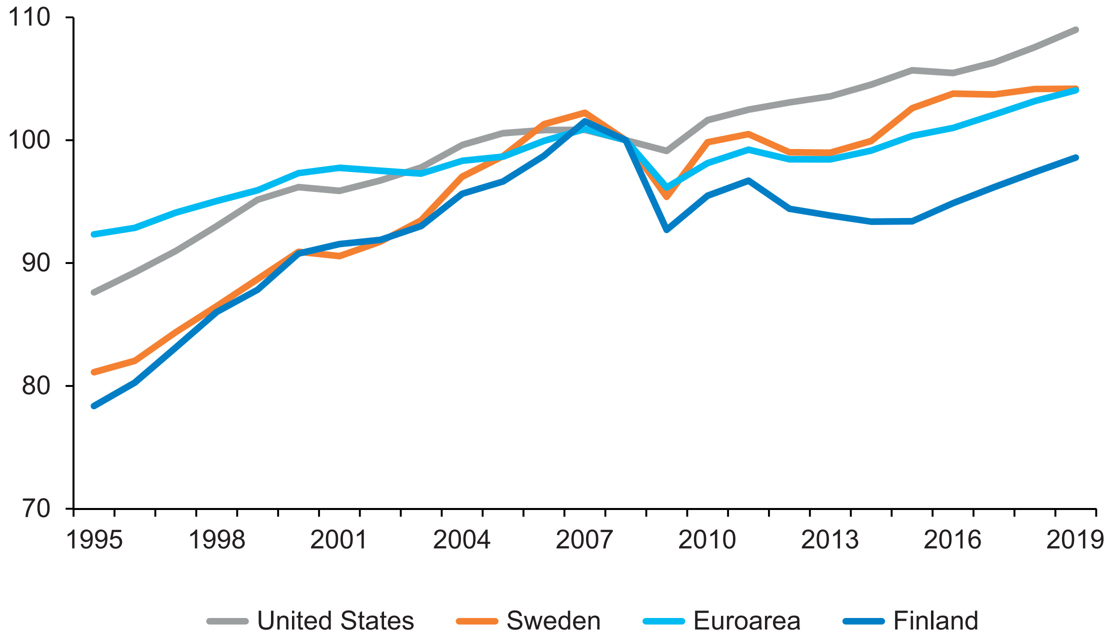
As discussed before, TFP is defined as the part of output growth that cannot be explained by input growth, with inputs typically defined as labor and capital inputs. The concept is also referred as the Solow residual, named after Solow (1956) who originally derived TFP as a residual of the Cobb-Douglas production function. While TFP captures the effects of changes in technology and other productivity shocks, the problem is that the variable is like a black box comprising all the potential productivity enhancements achieved in the economy, including also measurement errors. This gives little insights how to separate between different sources of productivity growth.

A key reason to why the analysis of TFP is important is that it has been a major source of business cycle variation in the recent years. Indeed, during the Great Recession its stagnancy has been a key factor behind the slow economic growth in many developed countries, including Finland and some of its important references. There has been a downward level-shift in this variable in several countries, as Figure 3.3 shows. However, because the TFP is affected by many influential factors, it is difficult to disentangle the nature and persistence of the gap.

The traditional explanation of the TFP swings is the variation in the utilization rate of capital. Fernald (2014), for example, points out that the unobserved variations are important over the business cycle. He refers to the literature that has found several reasons for this: firms hoard labor in downturns because they assess that the workers' skills are needed in the future upturn; firms reduce capital utilization, because it isn't worth paying a shift premium to get people to work at night, for instance; firms shut factories because the output produced from capital doesn't cover the costs of labor and materials. However, as put by Fernald (2014), the challenge is to derive a suitable proxy for unobserved variation of capacity utilization.

In addition to the capital utilization, the variation of TFP can result from many other factors. First, it can be traced back to the quality of the labor input. The jobs created during the downturn can be expected to be of lower quality for example due to the temporary nature of

Figure 3.3 Total-factor productivity in Finland and the key reference countries



Source: Ameco database.

the jobs, or because employees have to accept work that does not match their education. (see, e.g., Cœuré, 2017) Another literature argues that the TFP may fall because of variation of the research and development (R&D) activities during the crisis. This explanation relates both to the quality of labor if the phenomena manifests itself as cuts in the acquiring of skills, or productivity of capital in the form of less informed use of equipment. Indeed, the recent macroeconomic literature shows that in typical DSGE models it can be rational for individual firms to cut their R&D activities while at the aggregate level this behavior can lead to stronger business cycle variation of production, and in extreme cases even persistent stagnation (Benigno & Fornaro, 2018). In particular, while the technology itself may not be greatly affected by changes of innovation activities, the key driver of the variation may be the rate at which firms adopt new technology (Anzoategui et al., 2016)

To analyze the anatomy of the TFP, we assume in line with the previously shown empirical evidence that the production function of the Finnish economy is of the CES-form. In that case, the above problem is to some extent alleviated because the technological change is disembodied and factor augmenting. With this assumption technological progress leads to increases in the productivity of capital and labor at different rates, and as a result of the production function estimation, the capital augmenting and labor augmenting processes become observable.

Our contribution in this section is to estimate the cyclical and structural components of the two series simultaneously. Even though they are separate processes, it is reasonable to believe that they share a common cyclical component. For example, during the economic downturns the lowering of the capacity utilization of the capital stock tends to decrease the capital-augmenting productivity, but also result in the layoffs of the work force. The layoffs, on the other hand, may affect the quality of the continuing workers, as the employer is likely to keep the best workers. Thus, the labor-augmenting factor productivity changes. Similarly, the adaptation cycles of new technology are also likely to affect both the labor- and capital-augmenting productivity, while the relationship is less clear.

In addition to having specific TFP related challenges, the estimation shares many of the general problems that were already addressed in the discussion of the NAWRU estimation. The estimation has to take stand on the smoothness of the structural component that is determined by the signal-to-noise-ratio parameter, i.e. the ratio of variances of the trend and cyclical shocks. The larger the ratio, the more volatile the structural component is. The restrictions to the parameter space are again needed so that the cyclical component of the productivity is a stationary process, while the structural component is non-stationary. Furthermore, the methodology tends to impose mechanical rules on how fast the cyclical shocks die out, and thus the estimates of potential output are often correlated with underlying economic shocks that are cyclical, and thus seem to have a strongly cyclical component. (Coibion et al. forthcoming).

In case of measurement of the productivity, we again have to strike a balance between the restrictiveness of the identifying restrictions, and the flexibility of the model so that the data can “speak”. Thus, we use a Bayesian estimation method that uses the EC parameter estimates as informative priors. Furthermore, we provide additional information to the model about the relationship between productivity and factors that are considered to be cyclical. While we have considered different alternatives, we report how the variation of net exports affect our estimates. Again, we measure the shocks in the variables as the deviation of the variable from the past 3 years average. We introduce these shocks to the model as drivers of the unobserved cyclical component of the productivity.

3.4.2 Specification of the model

When the production function of the Finnish economy is of the CES-form, there are two multi-factor productivity series, one for labor-augmenting technological change, and the other for the capital augmenting technological process. We illustrate by using our new methodology how the separate components can be filtrated with a common estimation.

Unlike for unemployment and the Phillips curve, no precisely described theoretical model can be invoked to justify the breakdown to cyclical and structural components. Instead, it is assumed that the cyclical term depends on the under-utilisation of economic resources, which is measured using the capacity utilisation rate series. Furthermore, by making various assumptions about the duration of the effects of various shocks, it may be possible to identify the cyclical component of the overall factor productivity series.

The first dependent variable is the capital-augmenting productivity, which is broken down into a cyclical and structural component:

$$fp_t^K = p_t^K + c_t^K.$$

Since the cyclical component of the capital-augmenting productivity is dependent on the capacity utilisation rate, which in turn is dependent on the cyclical indicator, the connection between the cyclical component of total factor productivity and the indicator can be expressed as:

$$cu_t = \mu_U + \beta c_t^K + a_{cut},$$

where the lowercase letters indicate log-transformed variables. a_{cut} is a dynamic shock term that conforms to a AR(4) process with innovation variance V_{cu}^{a}.

The capital-augmenting productivity is driven by an undetected dynamic trend component, which in the case of Finland is expected to follow a dampened trend model

$$\Delta p_t^K = \mu_{t-4}$$

$$\mu_t^K = \omega^K(1-\rho^K) + \rho^K \mu_{t-4}^K + a_{\mu t}^K$$

$$c_t^K = 2A\cos\left[\frac{2\pi}{\tau}\right] c_{t-4}^K - A^2 c_{t-8}^K + a_{ct}^K$$

where μ_t. is an undetected trend component. The shocks $a_{\mu t}^K$ and a_{ct}^K follow a white noise process with variances V_μ^a and V_c^a. The cycle frequency τ and the cycle strength A are defined in the last equation (15) of the system of equations. ω^K is the average growth rate of long-term total factor productivity in the model.

We extend the model by introducing the labor-augmenting productivity to the model. After denoting it by fp_t^L, we impose the decomposition to the cyclical and structural component, p_t^L and c_t^L respectively:

$$fp_t^L = p_t^L + c_t^L$$

The labor-augmenting productivity is assumed to follow a smoothed-trend model

$$\Delta p_t^L = \omega^L(1-\rho^L) + \rho^L \Delta p_{t-1}^L + e_{pt}^L,$$

and the cyclical component is an AR model with a connection between the cyclical components of the labor-augmenting productivity and the capital-augmenting productivity:

$$c_t^L = \phi_{L0}\, c_{t-1}^K + \phi_{L1}\, u_{t-4}^K + \phi_{L2} u_{t-8}^K + \phi_{pr} c_{t-1}^L + e_{ct},\ e_{ct} \sim \mathrm{N}(0, V_{ec})$$

Finally, we allow an additional indicator equation that shares the same functional form as the capacity utilization indicator specification:

$$indicator_t^{ext} = \mu_{extra} + \beta_{extra} c_t^K + e_{cextrat},\ e_{cextrat} \sim \mathrm{N}(0, V_{ecextra})$$

3.4.3 Data

The factor productivity series are obtained from the production function analysis that was done in Section 2 where more details are given. The other considered indicators are the same as the ones used in the previous analysis concerning the estimation of the labor input. The data spans from 1991q1 to 2018q2.

3.5 Estimates of the NAWRU and the structural level of the participation rate

In this subsection, we discuss our results concerning the measurement of the labor input potential. We begin by showing the estimates of the potential and the trend components, and then we discuss in more detail the features of the underlying model and its estimation.

In Figure 3.4 we show the estimated NAWRU and its confidence intervals based on the state variance matrix of the Kalman filter. The figure suggests that our estimate of NAWRU is rather slowly moving. There is a gradual increase in the NAWRU during the 1990s crisis, while the increase stops in the early 2000s. The corresponding estimate of the participation rate is shown in Figure 3.5. The participation rate shows a decline during the 1990s crisis, while it has gradually recovered since 1998 until the onset of the current crisis.

Both variables suggest that the cyclical gap during the 1990s crisis was substantial, and its effect had a large and persistent effect on employment. This finding reflects the fact that both trend series are relatively smooth. The NAWRU estimate does not have the typical hump-shaped pattern that is often seen in the NAWRU estimates of the early 1990s. On the other hand, Figure 3.5 shows that the current participation rate trend estimate is smoother than estimate that is based on the HP filter (annual data and the standard smoothness parameter 6.25).

We next compare our estimates to the estimates provided by other institutions, especially the European Commission and the OECD. In terms of the NAWRU estimates, we focus first on the recent crisis and find that the EC estimates are rather close to ours. The OECD estimates, on the other hand, indicate that on their view the NAWRU is moderately higher than our estimates suggest.

The most striking difference between NAWRU estimates comes from how the Finnish NAWRU responds to the severe depression of the 1990s. According to our estimates, the Finnish NAWRU rate increased slowly, moderately, and with a lag in response to the depression. Therefore,

Figure 3.4 Estimate of the NAWRU based on the Kalman filter, and its confidence intervals (% of labor participants)

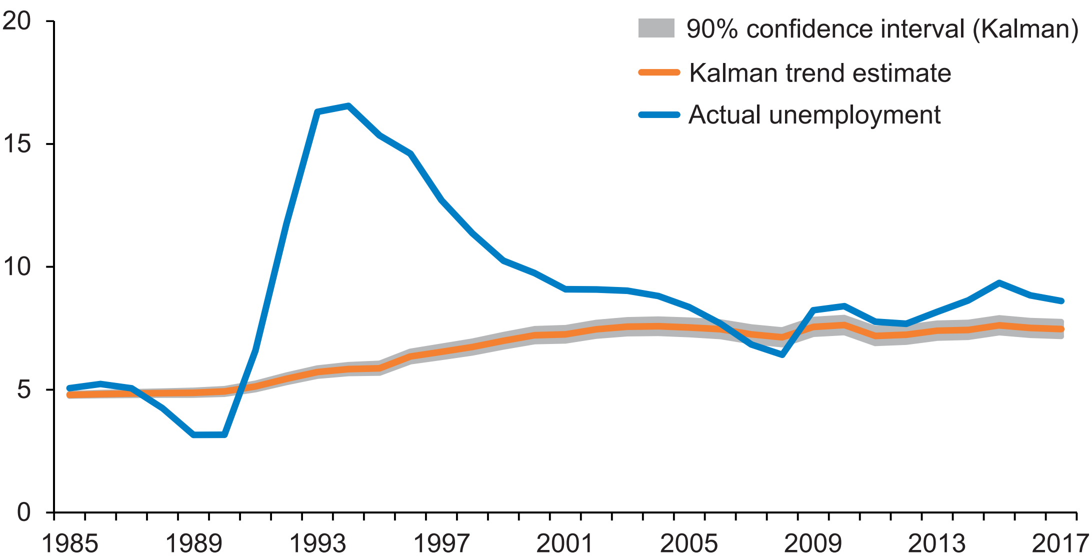
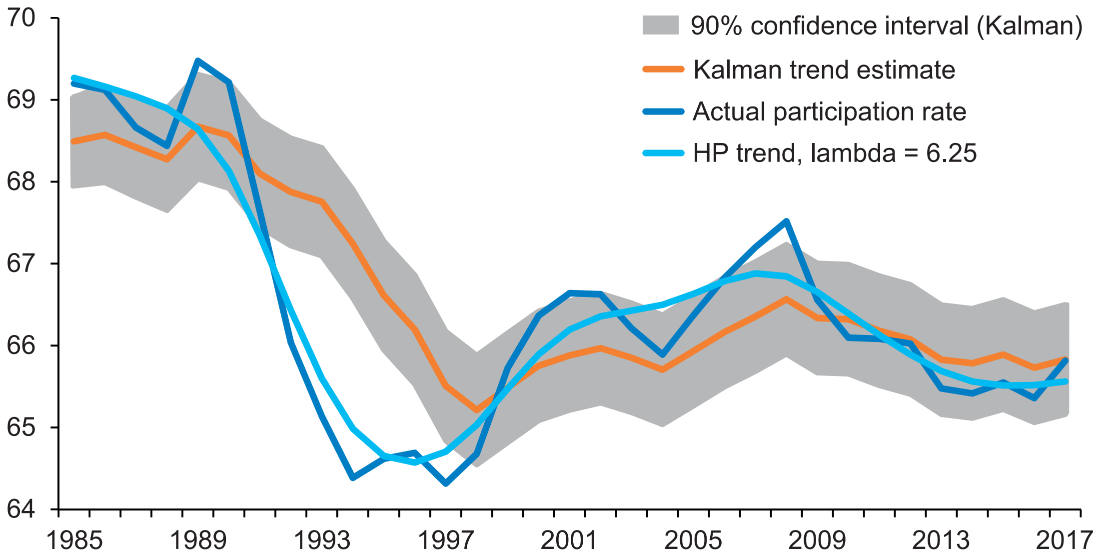


Figure 3.5 Estimate of the participation rate based on the Kalman filter, and its confidence intervals (Participation and trend estimates, % of working aged)



NAWRU is clearly less pro-cyclical than what the estimates of the European Commission and the OECD imply as Figure 3.6 shows. In fact, the estimates provided by these institutes suggest that the Finnish NAWRU reacted sharply upwards right after the unemployment began its expansion at the beginning of the 1990s. Then also, according to the international institutes' estimates, NAWRU fell in the late '90s as quickly as it had gone up before that, right after when the unemployment started easing off in Finland.

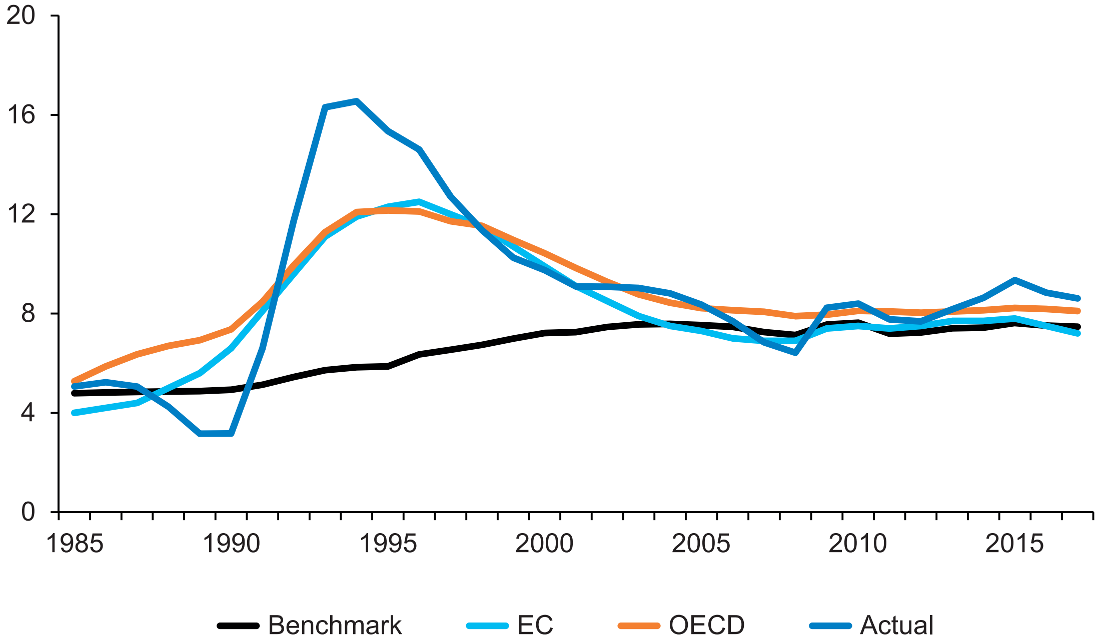
In case of the participation rate, we compare the gaps (between the actual and the potential) in our model and the EC model that is based on the HP filter in Figure 3.7. While there are some differences in the underlying participation rate series, the gaps nevertheless reflect well the dynamics seen in Figure 3.5: The HP-based EC estimates of the potential are less smooth than ours, and therefore the gaps between the actual and the potential are smaller, especially in the 1990s crisis. Having said that, the gaps are rather similar during the current crisis.

It is worth noticing that recently Kaitila et al. (2018) have studied the dynamics of the traditional Phillips curve in Finland and come to similar conclusions. Their finding is that the curve has been relatively stable during the current crisis which provides supportive evidence for a relatively stable NAWRU during the recent years which also provides supportive evidence for a stable NAWRU. Furthermore, Kaitila et al. (2018) used non-employment rate, ie. 1 – employment rate, instead of unemployment rate to analyze the labor market slack and wage increases in Finland. In this respect, they suggest that the Phillips curve has, to some extent, shifted downwards in time. This implies, together with the relative constancy of the traditional Phillips curve, that there is a gradual improvement in the labor participation rate.

We have also smoothed the states by means of backward recursion (see, e.g., Durbin & Koopman, 2012). In terms of both variables, the results indicate that the smoothed estimates are very similar during the current crisis. The smoothed NAWRU is, however, almost linear in the preceding time period. While this result indicates that according to our model the estimate of the NAWRU is almost constant over time, the rather extreme behavior is likely to result from the fact that model is estimated based on the likelihood of the Kalman filtered states, not the smoothed states. Thus, the smoothed shape of the NAWRU would likely to be closer to the Kalman estimates, had we proceeded differently in the estimation. While it is not clear which likelihood should be ultimately used, in case of the NAWRU it seems that the smoothed model may need a separate estimation.

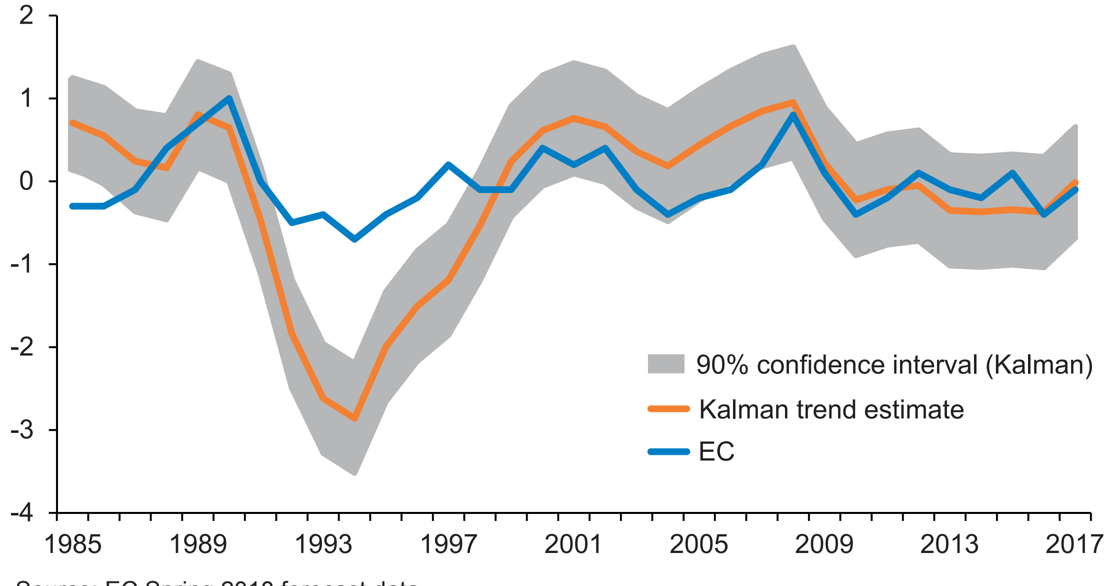
In order to analyze the dynamics of these variables in real time, we repeat the estimation with alternative datasets in Figures 3.8 and 3.9. We begin by considering the model out-

Figure 3.6 Estimates of the NAWRU based on the Kalman filter and estimates of the other institutions (Unemployment and trend estimates, % of labor participants)



Sources: Spring 2018 forecasts, Ameco and OECD database.

Figure 3.7 Estimates of the participation rate gap based on the Kalman filter, and the European Commission estimate (Participation gap, % of working aged population)



Source: EC Spring 2018 forecast data.

comes with dataset that spans until 2007q4, just before the crisis. We then repeat the estimation several times by extending the dataset by three years each time.

We find that especially NAWRU is subjected to large revisions. Just before the crisis, in the end of 2007, the model suggests that the structural unemployment estimate would have been considerably lower than currently. Given the rapid decline in the unemployment rate, it was probable that the structural unemployment rate would have been lower than the current level of unemployment, and the structural unemployment level would have been close to the level that was last seen before the 1990s crisis. In comparison to other countries, the suggested level would have been close to reaching the unemployment rates of countries like

Figure 3.8 Real-time estimates of the NAWRU based on the Kalman filter (Unemployment and trend estimates, % of labor participants)

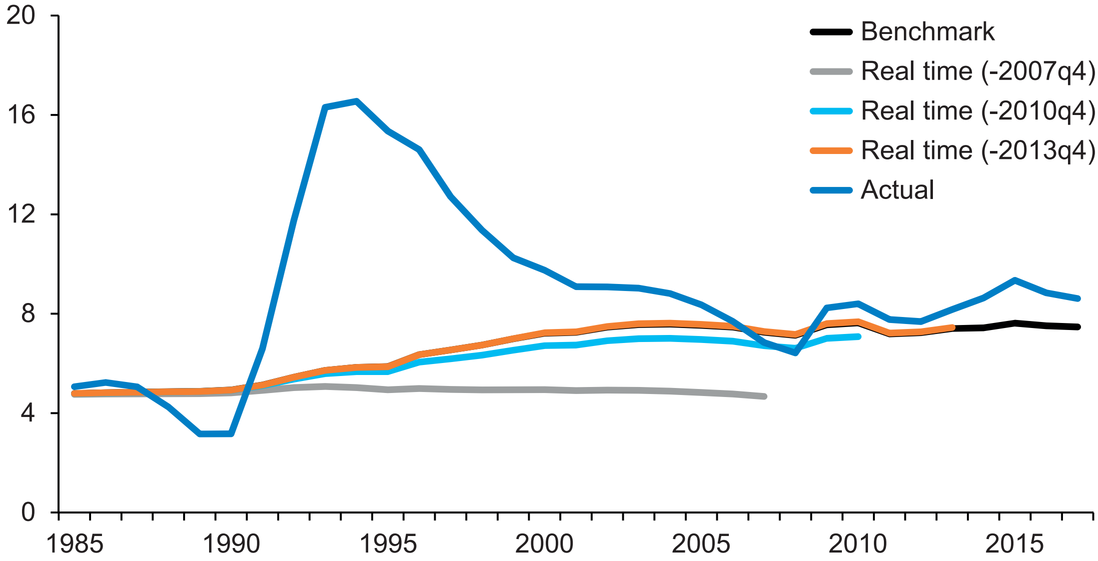


Figure 3.9 Real-time estimates of the participation rate based on the Kalman filter (Participation and trend estimates, % of working aged population)

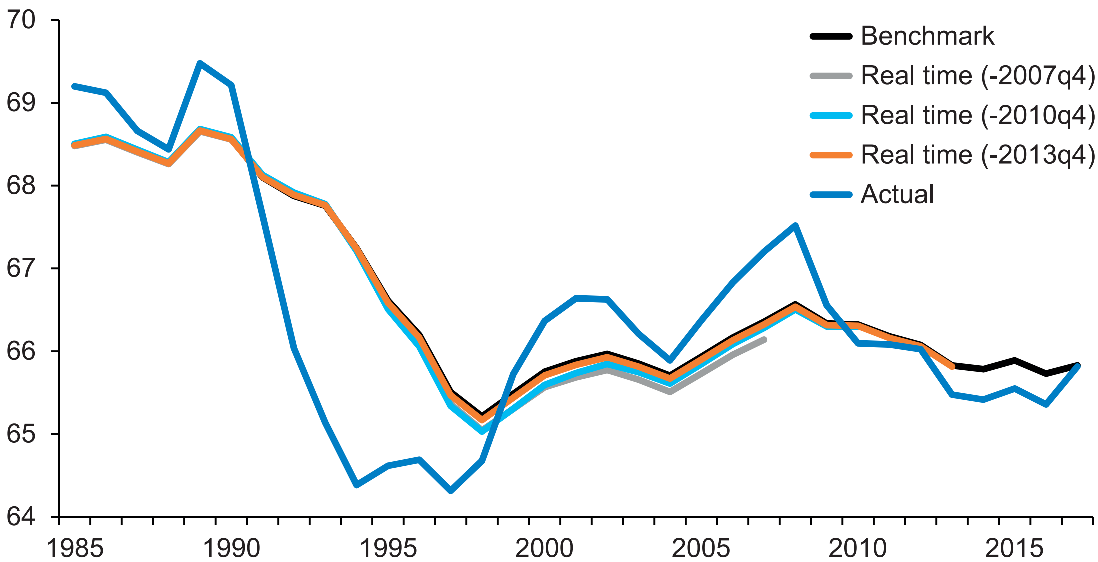
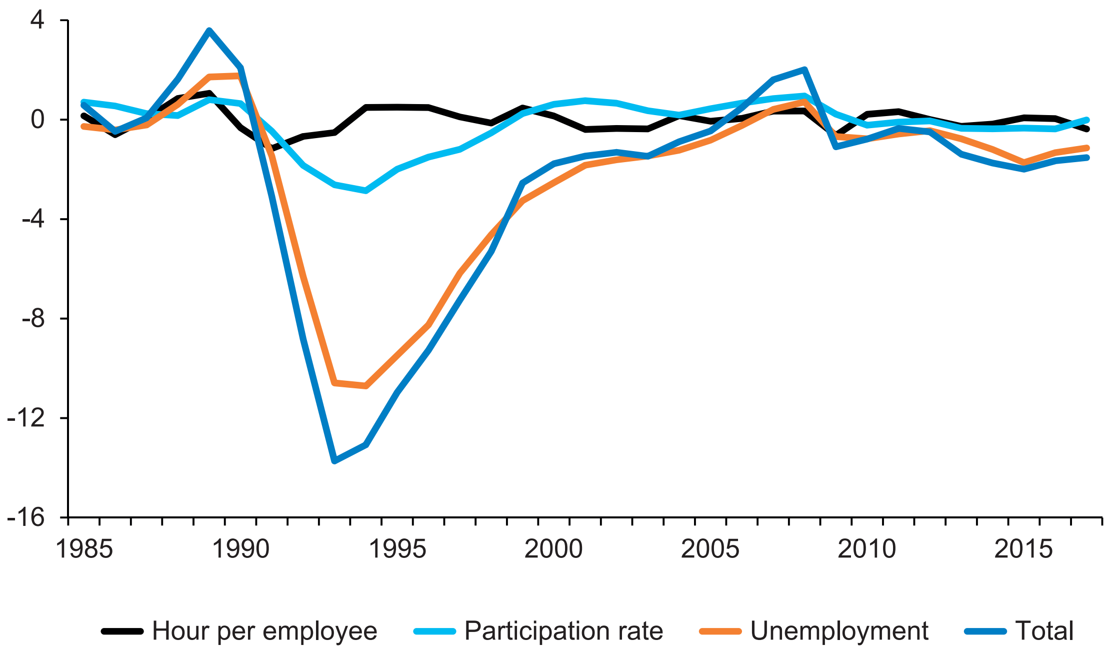


Figure 3.10 The total labor input gap and its components (Contribution to the cyclical variation of the labor input, % of total labor input)



Sources: Own calculations, Hours per employee: The Spring 2018 Forecast data, EC.

Norway and the US. After the crisis began, the NAWRU estimates increased sharply, and by the end of 2010 the estimate would have already been close to the current estimates.

Finally, we collect together the gaps between the potential and the actual level of the different labor input components and discuss their relative importance to total variation.[12] We find in Figure 3.10 that most of the cyclical variation has been due to the variation of unemployment. We further discuss the role of the labor input on total variation of output in Section 3.7

3.5.1 A closer look on the estimation of the model

A few details of the underlying parameters of the model, reported in Table 3.1, are worth discussing. First, we note that the key parameters of the model appear to be reasonable. On terms of the Phillips curve, the contemporaneous elasticity between inflation and unemployment gap is significantly negative ($\psi_0 < 0$). The effect is larger than in the European Commission spring 2018 forecast (-0.011), that is the closest reference to the current model. This suggests that the model indeed provides a strong Phillips curve relationship. When comparing the effect of forward-looking inflation expectations and the lagged inflation, the former seems to be larger, that is $\gamma_f > \gamma$. Together their coefficients exceed 1 implying together with a relatively large constant, α, that the influence of the expectations may be oscillatory.

In terms of the underlying shock variances, the model implies rather standard values. The variance of the cyclical unemployment, V_c, is relatively close to the value of the corresponding variable in the European Commission estimation, when it is taken into account that the Commission model is estimated by using annual data. The signal-to-noise ratio is 1/3.468 = 0.29 in the current model, whereas in the Commission model the corresponding value is

12 We further The hours per employee variable is taken from the EC spring 2018 forecast.

1/3.75,. The AR coefficients of the cyclical unemployment are also similar to the Commission estimates, and importantly, we find that the cyclical component is stationary.

The parameters of the participation rate are also worth discussing. In the model, there is a negative relationship between the cyclical component of the participation rate and the cyclical component of the unemployment rate. The prior distribution of the relationship is based on the correlation of the error terms between the HP filtered cyclical components of the two series. According to the model, a 10 pps increase in the cyclical unemployment decreases the cyclical component of the participation rate by 1 pps. The effect strikes as a reasonable one based on the magnitude of the cyclical variation in these variables.

The AR(1) coefficient of the cyclical component suggests that roughly 80% of the cyclical variation dies out in 4 years, which implies that the participation rate has a cyclical component with reasonable length of the cycle. The signal-to-noise ratio is moderately higher than in the case of the unemployment, 1/2.937 = 0.34.

A few technical details are worth discussed. First, we have tested how sensitive our results are to alternative choices of the prior distribution. In particular, we have considered a prior distribution that takes the key parameter estimates of the Commission's spring 2017 forecast as the prior mean while allowing for a reasonable large prior variance. Furthermore, we have extended the boundaries of the feasible parameter set, especially by allowing substantially higher

Table 3.1 The estimated posterior of the baseline model, the prior distribution, and the estimation boundaries

	Posterior		Prior			Estimation boundaries	
	Mean	Std. error	Mean	Std	Distribution	Min	Max
V_c	0.0794	0.0003	0.05	0.025	Inverse gamma	0	0.08
V_e	0.0022	0.0004	0.05	0.03	Inverse gamma	0	0.2
V_c / V_μ	3.4681	0.0246	3.5	0.02	Normal	2	5
ϕ_{c0}	0.1187	0.0109	0	0.01	Normal	0	0.2
ϕ_{c1}	1.3376	0.0109	1.3	0.01	Normal	-1.96	1.96
ϕ_{c2}	-0.6467	0.01	-0.7	0.01	Normal	-0.97	0.97
ψ_0	-0.0201	0.0025	-0.011	0.01	Normal	-2	0
ψ_1	0.0028	0.0014	0.0003	0.01	Normal	0	2
α	0.0324	0.0089	0	0.02	Normal	-1	1
γ	0.4421	0.0971	0.8	0.1	Normal	0	1
γ_f	0.7359	0.0893	0.8	0.1	Normal	-1	1
ϕ_{cpr0}	-0.1012	0.0056	-0.1	0.005	Normal	-1	0
$\phi_{cpr1} - \phi_{cpr0}$	0.0069	0.0029	0.002	0.005	Normal	0	1
ϕ_{cpr2}	0	0	0	–	Fixed	0	1
ϕ_{pr}	0.9059	0.0109	0.9	0.01	Normal	0.85	0.99
V_{ec}	0.041	0.0035	0.03	0.005	Normal	0	0.1
V_{ec} / V_{ep}	2.973	0.0568	3	0.05	Normal	2	5
β_s	0.1702	0.0224	0.168	0.028	Normal	0.1	1
β_{cap}	-0.0075	0.0009	-0.0073573	0.001	Normal	-0.1	0
β_{nexp}	0.0623	0.0188	0.047	0.02	Inverse gamma	0	1
V_x	0.1196	0.0183	0.09	0.03	Inverse gamma	0	1

Source: Own calculations.

cyclical shock variances. We report the alternative estimates of the NAWRU in Figure 3.11, and the corresponding vector of posterior parameter values and their distributions in Table 3.2.

Figure 3.11 The NAWRU with alternative prior specifications (Unemployment and trend estimates, % of labor participants)

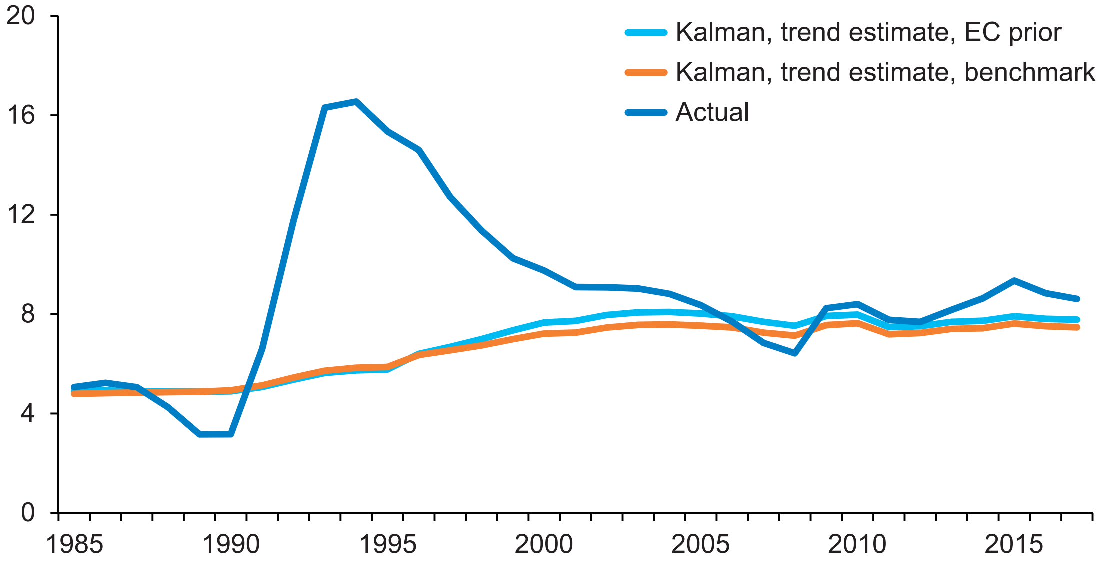


Table 3.2 The posterior parameter distribution after using the alternative prior

	Posterior, benchmark		*Posterior, EC Prior*		*EC Prior*			*Boundaries, EC specification*	
	Mean	*Std. error*	*Mean*	*Std. error*	*Mean*	*Std*	*Distribution*	*Min*	*Max*
V_c	0.0794	0.0003	0.6826	0.0143	0.43	0.025	Inverse gamma	0	0.7
V_e	0.0022	0.0004	0.0010	0.0001	0.0005	0.01	Inverse gamma	0	0.2
V_c / V_μ	3.4681	0.0246	3.1526	0.2283	3.76	0.25	Normal	2	5
$\phi_{c\,0}$	0.1187	0.0109	0.0179	0.0088	0	0.01	Normal	-0.2	0.2
$\phi_{c\,1}$	1.3376	0.0109	1.3769	0.0192	1.34	0.025	Normal	-1.96	1.96
$\phi_{c\,2}$	-0.6467	0.01	-0.6529	0.0185	-0.687	0.025	Normal	-0.97	0.97
ψ_0	-0.0201	0.0025	-0.0059	0.0012	-0.011	0.01	Normal	-2	0
ψ_1	0.0028	0.0014	0.0014	0.0010	0.008	0.01	Normal	0	2
α	0.0324	0.0089	-0.0124	0.0034	0	0.02	Normal	-1	1
γ	0.4421	0.0971	0.3477	0.0674	0.8	0.1	Normal	0	1
γ_f	0.7359	0.0893	0.5660	0.0697	0.8	0.1	Normal	-1	1
ϕ_{cpr0}	-0.1012	0.0056	-0.0992	0.0045	-0.1	0.005	Normal	-1	0
$\phi_{cpr1} - \phi_{cpr0}$	0.0069	0.0029	0.0032	0.0021	0.002	0.005	Normal	0	1
ϕ_{cpr2}	0	0	0	0	0	0.01	Fixed	0	1
ϕ_{pr}	0.9059	0.0109	0.9122	0.0090	0.9	0.01	Normal	0.85	0.99
V_{ec}	0.041	0.0035	0.0405	0.0028	0.03	0.005	Normal	0	0.1
V_{ec} / V_{ep}	2.973	0.0568	2.9976	0.0479	3	0.05	Normal	2	5
β_s	0.1702	0.0224	0.1756	0.0188	0.168	0.028	Normal	0.1	1
β_{cap}	-0.0075	0.0009	-0.0076	0.0007	-0.0073573	0.001	Inverse gamma	-0.1	0
β_{nexp}	0.0623	0.0188	0.0528	0.0138	0.047	0.02	Inverse gamma	0	1
V_x	0.1196	0.0183	0.0981	0.0115	0.09	0.03	Inverse gamma	0	1

Source: Own calculations, the prior for the NAWRU model is based on the estimated Spring 2018 model by the EC.

We find that the results are not very sensitive to the choice of the prior. However, we note that the alternative parameterization has features that are not desirable. In particular, the correlation between inflation and the cyclical unemployment is considerably lower than in our benchmark parameterization. All in all, this evidence suggests that the use of the restrictions of the variance parameter is a sensible choice, while it does not greatly affect our results.

Finally, we discuss the key features of our estimation procedure. First, we note that our estimates are averages of 25 SMC simulations, each simulation including 1 000 nodes. The individual simulations provide slightly different outcomes. The variation is particularly large in case of NAWRU. This suggests that, even with the rather informative prior that we use, the model seem to have rather irregular posterior distribution. While this uncertainty should be acknowledged when the results are interpreted, it also suggests that the use of the robust SMC method may be useful.

In terms of the functioning of the algorithm, it is worth noticing that the key test statistics indicate that the algorithm is typically functioning properly. The efficient sample size is found to be close to 800 with occasional resampling, and the Metropolis-Hastings algorithm reports acceptance rates that are desirable (around 0.3). In a few cases, however, we find that the estimator crashes. Typically, that is because the mutation step is not functioning properly anymore, and the posterior density becomes degenerate. In these cases, the MH algorithm reports that the acceptance rate has fallen to 0. We discard these simulations.

3.5.2 Alternative specifications of the Phillips curve

To build further intuition to our result, we start by considering the traditional wage Phillips curve in Figure 3.12. When spotting the combinations of unemployment rates and wage increases starting from year 1999 it is possible to observe the negative relationship between wage increases and unemployment rates. This type of the traditional Phillips curve seems to have slightly shifted downwards in time implying lower wage pressures at each level of unemployment, but all in all, the traditional Phillips curve relationship in Finland looks rather stable in time. This also suggests that major changes in the NAWRU have not happened.

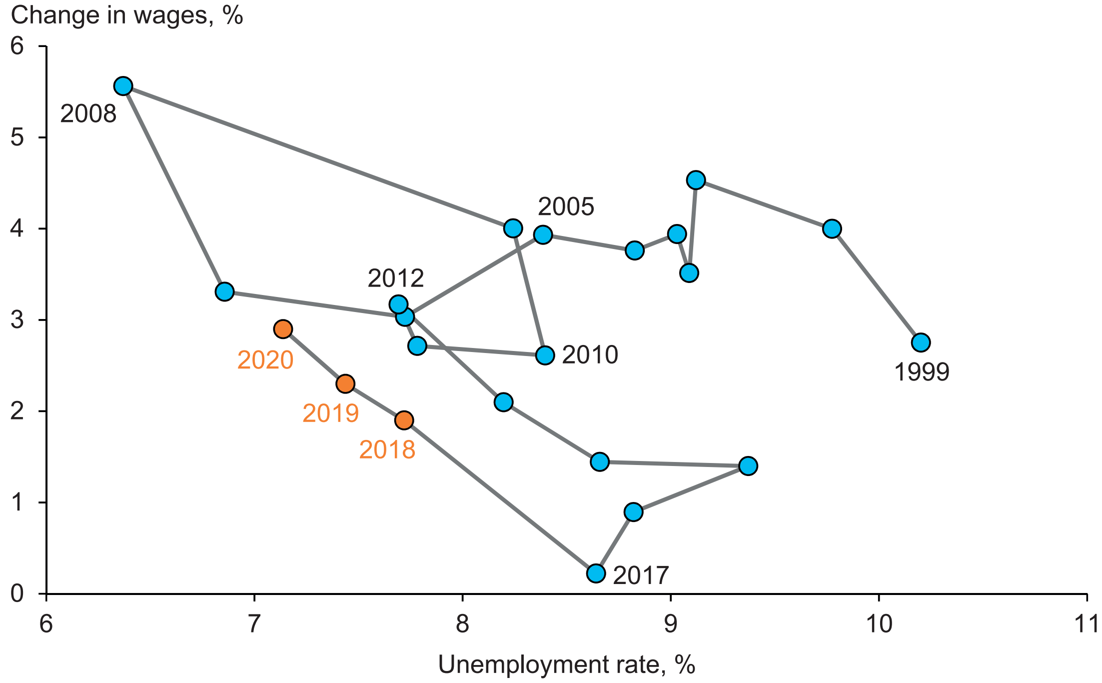
To analyze the robustness of our results, we have also estimated the model with alternative specifications of the Phillips curve. In particular, whereas our baseline model includes both the true, forward-looking inflation expectations (Eq. 2, "Benchmark"), and the backward-looking expectations, we also consider a Phillips curve without the forward-looking element (Eq. 1, "Perfect foresight"), and the anchored inflation expectations proposed by Rusticelli et al. 2015 (Eq. 3, "OECD nawru -specification").

We find that the inclusion of the forward-looking element has a relatively small effect on the estimates of the NAWRU. When the model is estimated after omitting the influence of the actual inflation expectations, there are only minor changes in the estimates of the NAWRU. On the other hand, the inclusion of anchoring of inflation expectations changes the NAWRU estimates more. In particular, when we fix the expectations of the RULC at its average level in 1995–2017, we find that the estimated NAWRU is roughly 0.5 pps higher than in the benchmark. This finding corresponds well with the differences between the OECD and EC estimates during the recent years[13].

13 It is noticeable that we have tested alternative levels of the anchoring, and our results seem intuitive: we find that when the anchor is placed on a higher level, the NAWRU, as indicated by the Phillips -curve, becomes smaller.

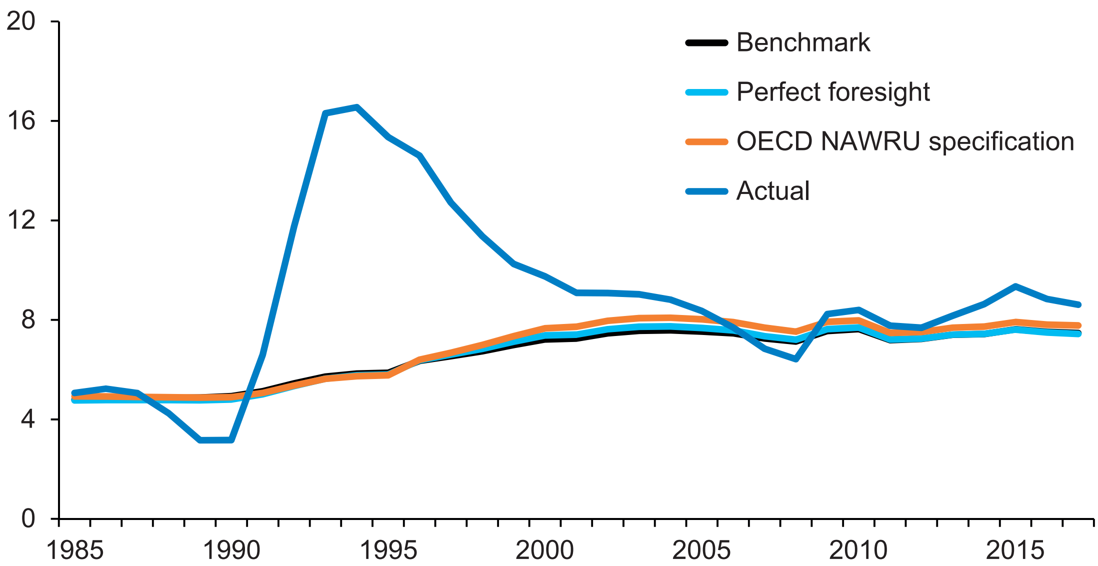
Based on the analysis, it appears that the measurement of the NAWRU by using the traditional Phillips curve (Eq. 1 and 2) is not very sensitive to the specification of the inflation expectations. Therefore, we are inclined to believe that the EC estimate provides a better view on the Finnish NAWRU than the OECD specification.

Figure 3.12 The traditional Phillips curve in Finland, 1999–2020



Sources: Statistics Finland and own calculations, 2018–2020 forecasts by Etla.

Figure 3.13 Estimates of the NAWRU under different assumptions concerning the Phillips curve (Unemployment and trend estimates, % of labor participants)



In order to produce yet an alternative, complementary estimate of the Finnish NAWRU, it is possible to exploit the idea of Llaudes (2005) according to whom NAWRU can be more accurately calculated with reference to an unemployment rate which places a lower weight on the long-term unemployed. Using this approach in the state-space specification of the accelerationist Phillips curve, ie. by imposing a lower weight on the long-term unemployed in line with their weaker ability to influence price and wage dynamics, produces NAWRU estimates that are less volatile and less cyclical when compared to the European Commission's estimates (see Lehmus, 2018). On average, the gained NAWRU series are also lower in levels.

3.6 Estimates of the labor- and capital-augmenting factor productivity

We next discuss our findings concerning the potential levels of the capital- and labor-augmenting productivity as well as their business cycle movement. In what follows, we assume in line with the previously shown empirical evidence in Section 2 that the production function of the Finnish economy is of the CES-form. The two factor-augmenting productivity series are based on the production function estimation with the benchmark "Statistics Finland" labor input series and the capital series with the six-tier investment classification (see, Section 2).

Our contribution in this section is to estimate the cyclical and structural components of the two series simultaneously. Even though they are separate processes, it is reasonable to believe that they share a common cyclical component, as already discussed before. For example, during the economic downturns the lowering of the capacity utilization of the capital stock tends to decrease the capital-augmenting productivity, but also result in the layoffs of the work force. The layoffs, on the other hand, may affect the quality of the continuing workers, as the employer is likely to keep the best workers. Thus, the labor-augmenting factor productivity changes. Similarly, the adaptation cycles of new technology are also likely to affect both the labor- and capital-augmenting productivity, while the relationship is less clear.

The estimates of the potentials and their confidence intervals are reported in Figure 3.14 and Figure 3.15. During the estimations, we use the SMC methodology and the EC priors. In particular, the prior distribution for the parameters of the capital-augmenting productivity are taken (consistently with our model structure) from the Spring 2018 EC forecast. It is noticeable that during the simulation we have transformed the capital-augmenting series so that its mean matches with the Commission's TFP series. That is, because we want to minimize the risk that the level of the series would affect the use of the Commission priors.

The results suggest that the capital-augmenting productivity is a key driver of business cycle variation. Concerning the current crisis and its recovery, the estimates suggest that there was a peak in the business cycle in the mid-2000s, and subsequently a large reduction in the productivity of the capital use. After the short recovery in the early 2010s, there was a second contraction. Finally, after 2016, the economy has reached a new upturn, as the productivity growth of the capital use has recovered.

On the other hand, we do not find clear evidence on a strong cyclical behavior of the labor-augmenting productivity. During the recent crisis, there has been a marked decline in the growth rate of the variable, but this decline of growth is neither clearly associated to the common cyclical component of the two productivity series nor to the cyclical shocks that could have directly influenced the labor-augmenting productivity.

Then, the model is estimated separately for different subintervals of the data. We start by re-estimating the model with data that spans until 2007q4, and then expand the dataset in steps, by adding three more years to the data each time.

It is noticeable that the capital-augmenting productivity estimates are relatively stable. Even if the dataset is considerably shorter, including the data only until the year 2007, the estimates are within a small distance from the benchmark estimates. Moreover, we compare

Figure 3.14 Estimated state of the potential capital-augmenting factor productivity, log-scale

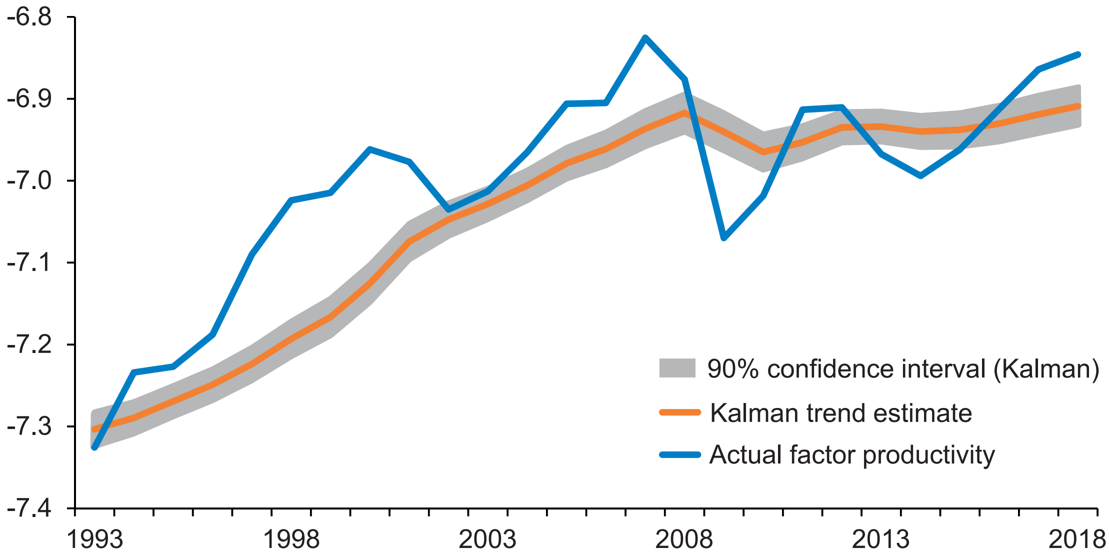
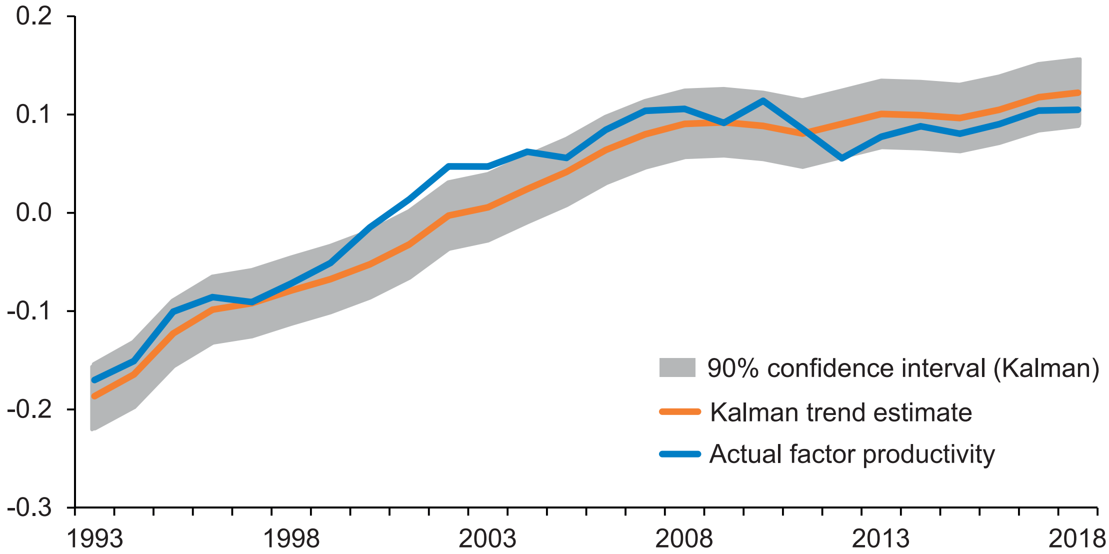


Figure 3.15 Estimated state of the potential labor-augmenting factor productivity, log-scale



the estimates to the smoothed states in the Appendix of this section. The result indicate that Kalman states (building on the estimated model, but using in each data point the data that spans only until the corresponding point) are relatively close to the smoothed states.

On the other hand, the labor-augmenting productivity is prone to larger revisions, at least when considering the relative changes in size of the gap estimates over time. The consideration of the smoothed states makes the impression even stronger: they are considerably more stable than the estimates based on the Kalman filter.

Finally, in order to compare our productivity estimates to those of others, especially to the EC, we first provide an estimate of the aggregate TFP gap. We measure the aggregate TFP

Figure 3.16 Real-time estimates of the capital-augmenting factor productivity, log-scale

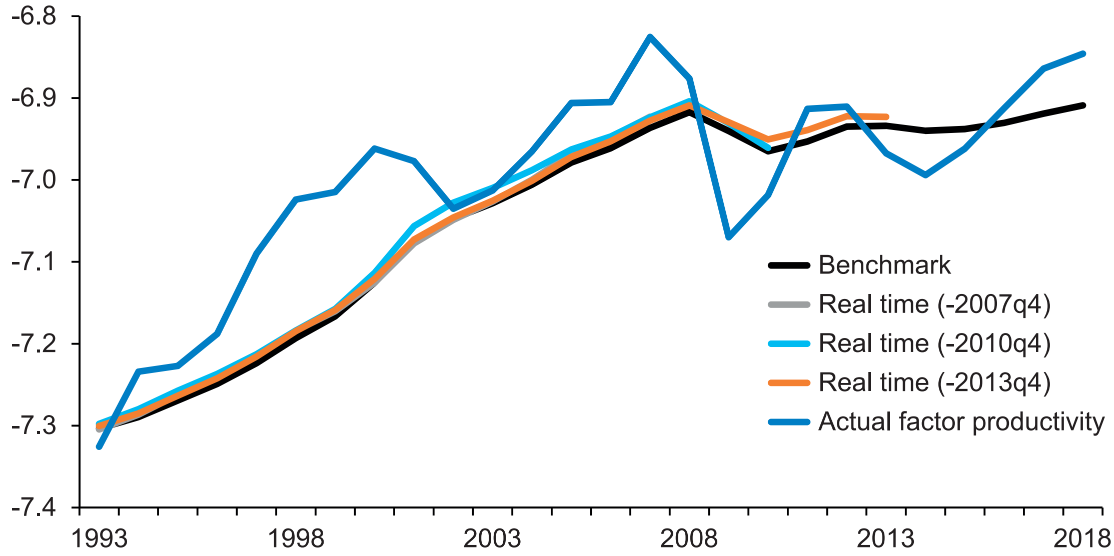


Figure 3.17 Real-time estimates of the potential labor-augmenting factor productivity, log-scale

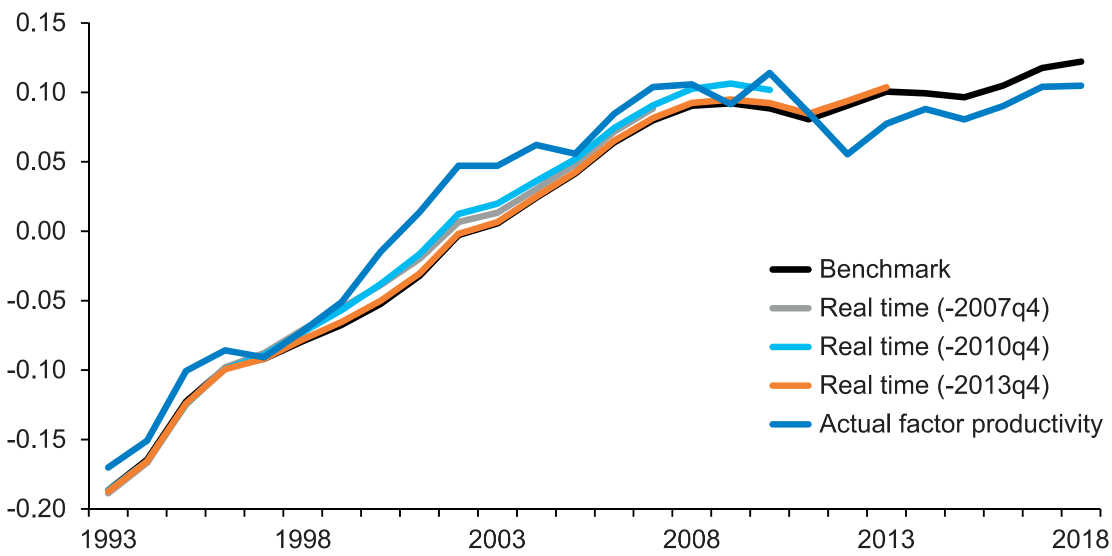
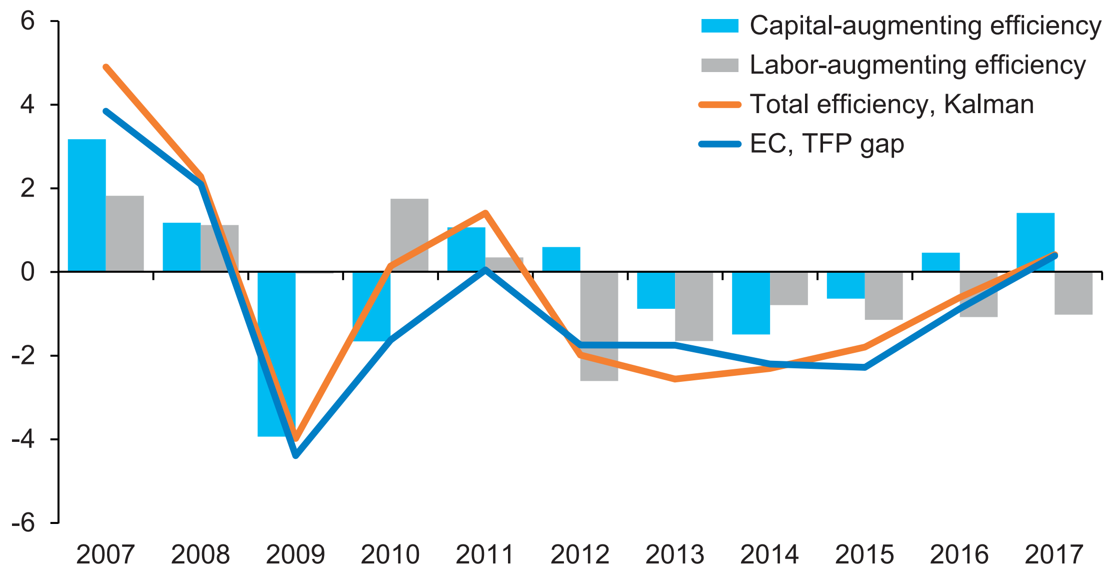


Figure 3.18 The contribution of the total productivity (capital and labor) and European Commission TFP gap to GDP, % of potential GDP



by comparing the value of the production function at the potential level of productivity of the both factors, and then at the actual level of the productivities. The difference yields an estimate of the total effect of TFP to the output gap.

We find in Figure 3.18 that during the current crisis the estimates are rather similar, while it seems that the current estimation implies moderately larger swings in the business cycle.

We further decompose the productivity effect into capital- and labor-augmenting components that are reported as bars in Figure 3.18. We consider the partial effects by augmenting the production function only with one factor productivity at a time. We find that prior to the crisis the upswing was mainly due to the capital-augmenting technological change. On the other hand, the 2009 contraction was due to a dip in the capital-augmenting productivity, while the latter part of the crisis was more due to the labor-augmenting productivity.

Finally, we note that especially at the beginning of the 2000s our total productivity gap generates relatively large positive output gap. The contributions are mostly explained by high levels of capital augmenting technological change in the early 2000s. We discuss these observations in the next section but note that the behavior of the model at the late 1990s and early 2000s may be partly a result from the fact that the data starts only at 1991.

We further discuss the implied output gaps in historical context in Section 3.7.

3.6.1 A closer look on the estimated parameters

We next analyze the key parameters of the model in more detail. First, we find that the estimated elasticity of the capital-augmenting productivity, FP^K, with respect to changes in the capacity utilization rate is moderately smaller than in the EC prior (spring 2018) that we also use as our prior. One log-unit change in the cyclical productivity changes the capacity index by roughly 1.3 units. By reversing this relationship, the result indicate that our model's cyclical component of the FP^K is more sensitive to changes in the capacity utilization than the prior suggests.

Our estimation shows that the amplitude of the cyclical component of the capital-augmenting technological change, A, is smaller than the prior of the European Commission for the total TFP. The average length of the business cycle is 5 years in our model, a moderately longer time span than the commission prior. The signal-to-noise ratios in the models suggest that for both variables the ratio is of the same magnitude, but somewhat smaller than the European commission uses in its Spring 2018 forecast for the TFP.

In terms of the covariation between the two productivity series, we find that the cyclical fall in the FP^K has contemporaneously a moderately lowering effect of on the FP^L, while on a one-year horizon the effect turns into an increase in the TFP^L. In the two-year horizon the effect is again decreasing. We find that these relations are qualitatively similar to the findings by Kauhanen & Maliranta (2017) who argue that the inverse relationship may result from changes in the decomposition of labor during the economic crises.

Finally, it is worth noticing that the SMC algorithm is typically functioning properly. In the estimation of the productivity components, we again take the average of 25 SMC simulations and use 3 000 particles in each estimation. The efficient sample size is found to be of sufficient size as compared to the total number of particles, and the Metropolis-Hastings algorithm reports acceptance rates that are desirable (around 0.3). In a few cases, however, we find that the estimator crashes in which case we omit the results.

Table 3.3 The parameters of the productivity model: Estimated posterior, the prior, and the boundaries for the estimation

	Posterior		*Prior*			*Estimation boundaries*	
	Mean	*Std. error*	*Mean*	*Std*	*Distribution*	*Min*	*Max*
β	1.3327	0.0241	1.4	0.02	Normal	0	5
A	0.2719	0.0223	0.322	0.02	Normal	0	1
τ	35.2166	0.4349	32	1	Normal	2	120
ρ^K	0.8315	0.0091	0.8008	0.01	Normal	0	0.98
ω^K	0.0061	0.0006	0.0038	0.0005	Normal	0	0.03
δ^K	0.0136	0.0125	0.0004	0.01	Normal	-0.1	0.1
V_c^a	0.0010	0.0000	0.0001	1.00E-05	Inverse gamma	0	0.001
V_μ^a	2.87E-06	9.97E-08	1.00E-06	1.00E-07	Inverse gamma	0	3.00E-06
V_{cu}^a	0.0058	0.0002	0.002	0.0002	Inverse gamma	0	0.006
μ_U	-0.0284	0.0083	0.0004	0.01	Normal	-0.1	0.1
ω^K	0.0031	0.0008	0.00286	0.001	Normal	0	0.03
ρ^K	0.8529	0.0122	0.85	0.01	Normal	0	0.92
ϕ_{L0}	0.0718	0.0197	0.046	0.02	Normal	-2	2
ϕ_{L1}	-0.1083	0.0203	-0.118	0.02	Normal	-2	2
ϕ_{L2}	0.1300	0.0205	0.142	0.02	Normal	-2	2
ϕ_{pr}	0.7855	0.0318	0.8	0.025	Normal	0	2
V_μ^e	1.70E-06	5.27E-07	1.00E-06	1.00E-07	Inverse gamma	0	3.00E-06
V_c^e	0.0003	0.0001	0.0001	1.00E-05	Inverse gamma	0	0.001

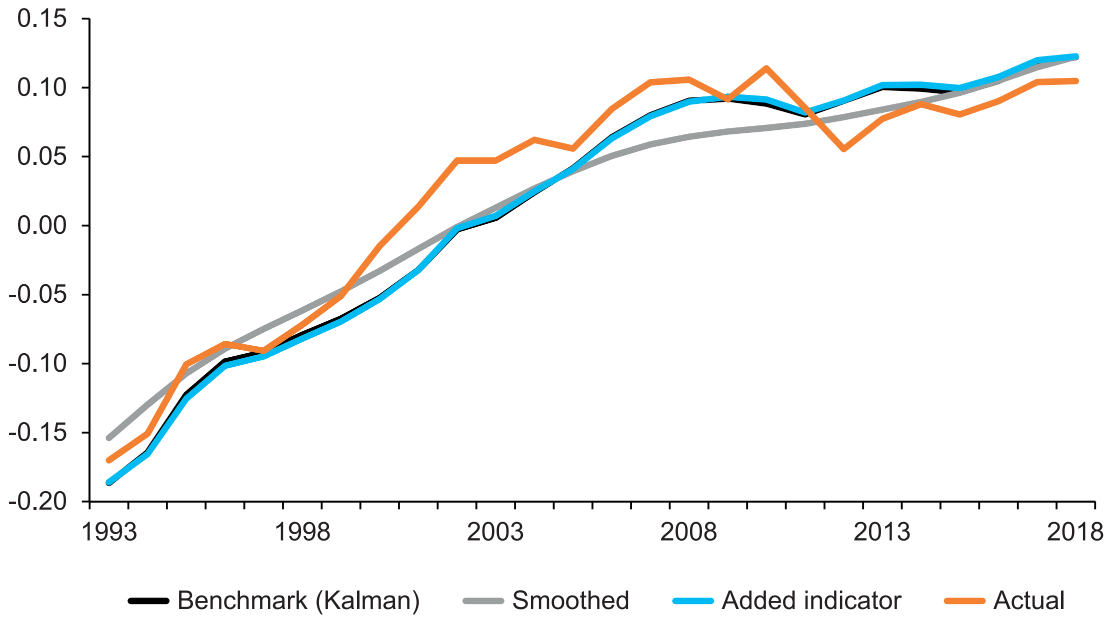
Source: Own calculations, the prior for the capital-augmenting productivity model is based on the estimated Spring 2018 model by the EC.

3.6.2 The role of other business cycle indicators in the identification

We have also investigated the possibility to use additional cyclical factors to provide extra information considering the business cycle. In case of the productivity estimations, it is noticeable that our baseline specification already uses the capacity utilization indicator as an identifying variable in a manner that is similar to the EC's estimation. We consider an additional indicator equation that has the same structure as the capacity utilization, and as the indicator variable we choose between the net-exports-to-GDP ratio and the interest rate spread.

We find that while the series are correlated with the capital-augmenting productivity, there is a considerable amount of noise in the relationships. Thus, we cannot use very informative priors, and the effect of the indicator variables on the estimated states are negligible, as Figure 3.19 that uses the net exports as an additional indicator shows.

Figure 3.19 The impact of using an additional indicator in the estimation (Productivity (labor) and trend (log-scale))

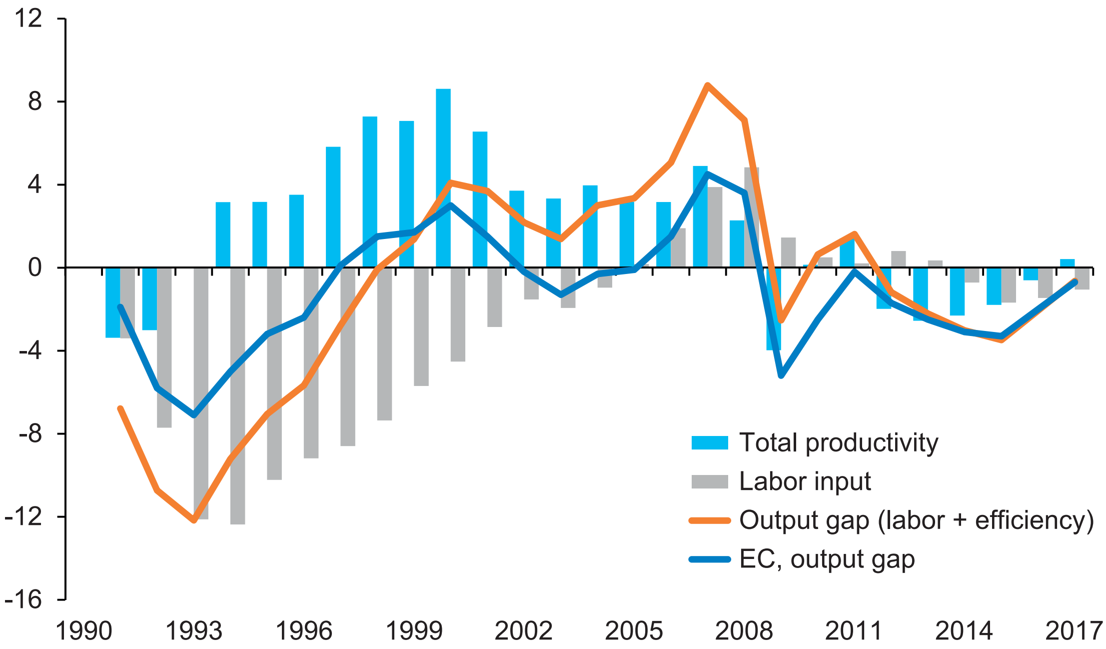


3.7 The output gap

In this subsection, we collect the information concerning the Finnish output gap together from the previous sections. Figure 3.20 shows the output gap based on our perceptions concerning the labor gap and the total productivity gap. The latter we estimate by introducing the capital- and labor-augmenting productivity gaps to the production function that was estimated in section 2. The labor gap is measured by summing up the unemployment gap, the participation rate gap, and the total hours per employee gap (which we take as given from the EC spring 2018 forecast). The joint effect of productivity and labor input on the production function yields the output gap.

In terms of the current economic downturn, our results indicate that the economy suffered from a double dip recession. The first dip was observed in 2009 when the economy reached

Figure 3.20 The output gap and its components (% of potential GDP)



Source: The used output gap is from the European Commission spring 2018 forecast.

a -2.5% output gap. After recovery by 2011, the economy faced another contraction that pushed it back to a similar sized output gap. By 2017, the gradual recovery has removed the output gap. While the Great Recession is a prolonged crisis, the Finnish Great Depression of the 1990s still strikes as the most severe economic crisis with output gaps being twice the size of the gaps during the current crisis. According to our analysis, a major difference between the two crises was that the Great Recession was for a large part driven by the factor productivity component, whereas the 1990s crisis was predominately driven by the unemployment of labor.

When compared to the European Commission estimates, our estimates imply larger effects of the business cycle for most of the peak and throughs of the Finnish business cycles. For the recent years of the Great Recession, our findings suggest that the output gap has been similar to the Commission's output gap estimates. On the basis of the analysis in Section 2, it appears that most of the differences are due to the use of our SMC methodology rather than the Commission's output gap methodology.

The narrative of the Finnish Great Depression cycle is also somewhat different. Our results imply that the labor and productivity cycles were strongly asynchronous: Throughout the late 1990s the economy faced a large and persistent labor input gap that exceeds the estimate of the EC, and the gap closed only in the early 2000s. On the other hand, the total productivity gap was small during the crisis, while its effect turned strongly positive in the late 1990s. Due to the upswing, the output gap vanished by the year 1997 and thereafter the economy faced a relatively large and persistent productivity driven upturn that came to an end at the onset of the Great Recession.

Finally, we note that we have also conducted similar decomposition by using the smoothed estimates of the states. We find that the results remain qualitatively similar.

3.8 Concluding remarks on the estimation of the potential output and the output gap

In this section, we applied novel filtration methods in order to further analyze the cyclical sensitivity of the elements of the production function. In particular, we applied the Sequential Monte Carlo (SMC) method to analyze the cyclical co-variance of the labor input and the capital augmenting efficiencies. In addition to the cross-variation of the different components of the production function, we also used various indicators of the business cycle, as well as used detailed Phillips curve specifications.

We first applied the SMC method to investigate the potential level of the labor input. While we used the Phillips curve to identify the non-accelerating inflation rate of unemployment, we simultaneously modelled the cross-variation of the cyclical components of unemployment and the labor-force participation rate, as well as other cyclical factors to jointly identify the business cycle. Furthermore, we augmented the EC Phillips curve with true, forward-looking expectations, and the anchored inflation expectations proposed by Rusticelli et al. (2015). The estimation was conducted by using Bayesian estimation, while using the Commission estimates as the starting point for choosing priors.

We found that the model identify reasonable estimates for both the NAWRU and the potential level of the labor force participation rate. While the estimates are relatively similar during the Great Recession, we note that our estimates are considerably smoother during the Finnish Great Depression of the 1990s. Thus our findings provide evidence against large and short-lived variation of the potential labor input during economic crises, which both the EC and the OECD estimates seem to indicate. We found that the results of the model are not very sensitive to the choice of the Phillips curve, while they indicate that the EC methodology may be preferable to the OECD method. Finally, our results indicate that some restrictions to the signal-to-noise ratios of the filters are warranted to ensure that the potential estimates have theoretically desirable properties.

As a second application of the SMC, we analyzed the cyclical cross-variation of the capital and labor augmenting productivity. We found empirical evidence that there is a countercyclical element to the labor augmenting productivity. That is, when the capital augmenting productivity falls, the labor augmenting productivity reacts by increasing. The most natural explanation is that when the capacity utilization of capital falls, it is accompanied by layoffs of the workers that tend to increase the productivity of the continuing workers.

All in all, the results of our SMC analysis suggest that the influence of the business cycle on the Finnish economic activity may have been larger than the European Commission method would suggests. We also found that especially the NAWRU and the labor augmenting productivity are very sensitive to the real-time uncertainty, and therefore we suggest that the economic policy should not only be assessed based on the statistical estimates, but rather also finding anchors for the potential of the labor market from other data, and in particular, from the labor market outcomes of the Finnish reference countries. We return to this analysis in the following section.

4 PROJECTIONS OF THE MEDIUM-TERM GROWTH POTENTIAL FOR FINLAND

Tero Kuusi and Markku Lehmus

In this section, we discuss the medium-term growth potential of the Finnish Economy in the years 2019–2023. Our analysis builds on structural macroeconomic modelling. While the estimates of the potential output in the previous sections provide the potential estimates at the (end)points of existing data, the structural approach is used to extrapolate the economic dynamics over time as a response to changes in the longer-term drivers of growth, such as technology and population growth.

In what follows, we make use of a multi-sector neoclassical growth model that incorporates forecasts of total-factor productivity changes, resources of the economy, as well as the conditions for external trade into a coherent forecast of the economic growth. The details of the model are available in the Box 4.1 and the Appendix. The model's growth potential is based on the optimal use of resources in a frictionless economic environment and thus fits well with the definition of the potential. The economic agent of the model responds to changes in the economic environment by saving, consuming and investing according to a well-defined goal to maximize utility. The optimizing behavior allows to make structural forecasts that are consistent with the optimal behavior even if the forecast horizon gets longer and the economic environment changes.

We employ the model to make forecasts regarding the economic growth and its stability, as well as the movement of resources between sectors. Furthermore, the structural model allows us to dissect the different elements of growth and helps to understand its anatomy. The baseline of the model is calibrated to match the key structural growth factors that determine growth. The labor input grows according to the forecasted growth of potential hours. The total-factor productivities as well as the market sizes and prices grow at constant rates that are matched with historical data. The Finnish ICT sector faces a period of rapid productivity growth in the 2000s that is followed with a return to normal trend. This effect represents the influence of Nokia in the model.

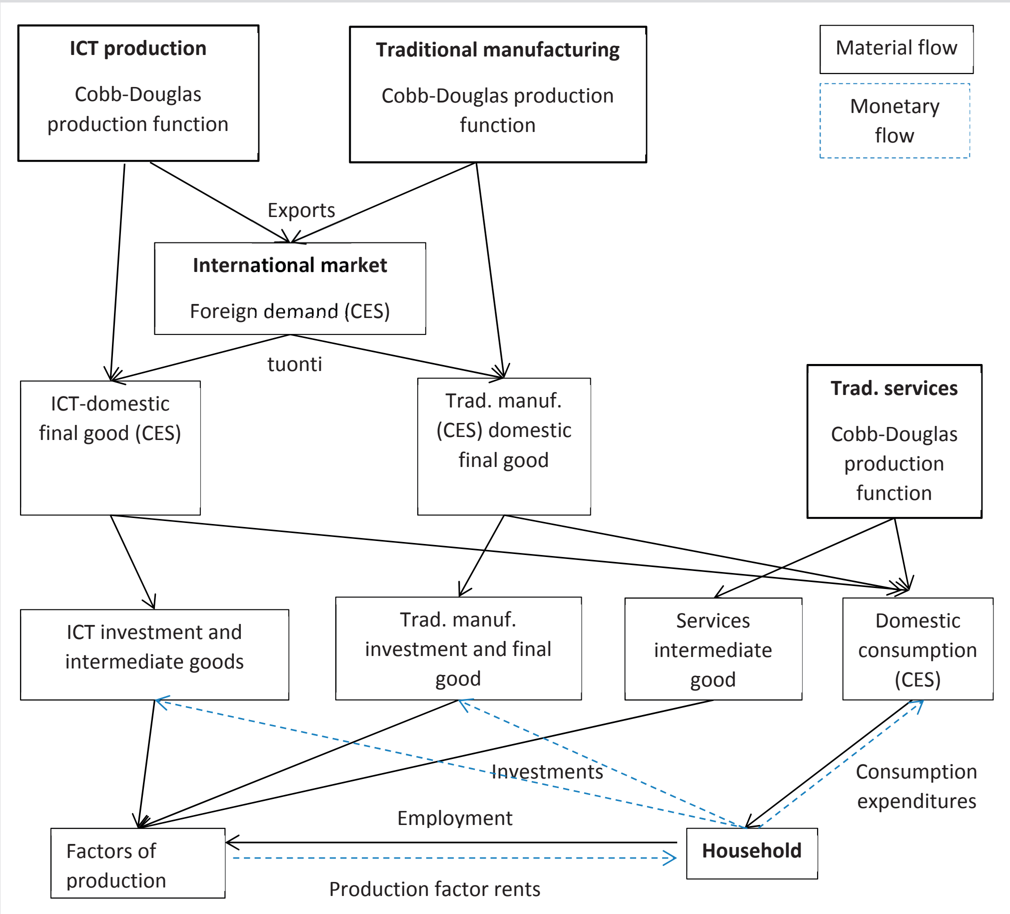
While we build our baseline to the conservative predictions of the key drivers of growth and the corresponding model outcomes, we also discuss alternative scenarios that involves different levels of productivity and labor input growth. As the previous analysis of the statistical properties of the potential output suggests, sharp and large revisions of the key variables are possible, and therefore the economic forecasts and policy should not be built on a single scenario. We discuss the alternative scenarios in Section 4.3.

Box 4.1 The multi-sector growth model

The model economy operates at the potential level of the economic activity. The products that are manufactured domestically or imported are at all times allocated to the best possible use either to serve as production factors, consumption goods or exports. There is a representative household in the economy that owns the firms and makes decisions to either consume or save the labor and capital income that it receives from the firms. The labor input and population is assumed to be exogenous and governed by the available forecasts. Recent references to the multi-sector growth modeling are Fernald (2016) and Jorgenson (2016). A good introduction to the modeling is given by Roe et al. (2010).

The outline of the model is presented in Figure 4.1 The model economy consists of sectors producing ICT, traditional goods, and traditional services.[14] Each sector has a unique Cobb-Douglas production function with industry-specific factor intensity shares and multi-factor productivity terms, which are calibrated using the National Accounts.[15]

Figure 4.1 Outline of the multi-sector model



14 ICT = ICT related manufacturing and services; traditional services = private and public services; traditional goods = other industries.

15 It is worth noticing that the sectoral C-D assumption is used because the nominal factor shares of the inputs are relatively constant at the sectoral level. Moreover, the assumption is not a priori inconsistent with the CES aggregate production function. That is, because (1) the demand functions in the model have the CES form, and (2) adjustments in demand affects the use of production factors due to heterogeneity in the use of capital and labor across sectors, and (3) the demand effect is similar to the effect that the use of the aggregate CES production function would generate.

The sectors produce sector-specific intermediate and capital goods, the difference being that intermediate goods have to be used during the period of its production. There are two capital stocks based on ICT and traditional goods. The household is assumed to consume sector-specific goods according to a CES aggregator.

The firms engage in international trade, and the patterns of trade reflect the comparative advantage of countries in different sectors. Especially the changes in the competitiveness of trade in high-tech goods and services in exports is modelled closely to analyze the role of the Finnish ICT sector. Tradable sectors consist of heterogeneous firms and sector-specific goods are composites of firm-level goods produced either in a domestic country or abroad. Distribution of firm-level productivities is modelled in a manner that makes it easy to estimate unit costs of foreign countries and trade barriers. The size of the foreign market and unit costs abroad are taken to be exogenous.

The baseline growth path is calibrated to match the key structural changes in the Finnish economy. The total-factor productivity growth rates are close to their historical averages, the population and employment growth is matched with the medium-term forecasts, and the external market is calibrated to match the structure of the exports and the share of imported products in the domestic market. The model is matched with the sectoral shifts of the consumption and value added, as well as movement of labor across sectors.

During the exercise, several counterfactual scenarios are considered in which some of the underlying growth factors are either switched off or on. The resulting changes in the growth paths are studied in order to quantify the impact of the factors.

4.1 The determinants of the potential output growth in the model

In this subsection, we introduce the key drivers of the Finnish economy through the lens of the model. The details of the calibration and modeling choices are left to the Appendix of this section.

As typical in the structural growth models, the key driver of economic growth are technological changes, as measured by the total-factor productivies in the sectors. We acknowledge that the technological changes are only approximate explanations for economic growth, while the fundamental drivers are for example innovations, accumulation of knowledge, diffusion of technology, and the institutions that allows the drivers to function. However, we argue that in the current context the TFP growth can well approximate the effects of these underlying growth factors[16].

In particular, our model allows us to incorporate the rapid technological progress in information and communications technology (ICT). The technology facilitates wide-spread reorgani-

16 We have introduced a version of this model that endogenizes the observed TFP growth in Ali-Yrkkö et al. (2017), but in terms of the growth implications, the results are the same.

zation of production in sectors using the new technology and gives rise to an expanding production of high-tech goods and services. Understanding how the new technology spills over to the surrounding economy is crucial to understand the long-term growth implications of the new technology. The access to cheaper technology increases welfare of the consumers, and the development of production technology affects production and investment decisions of the firms. Most visibly, the impact of the technology can be seen as a rapid decrease in the relative price of the new technology. In the model, this effect arises from the productivity growth in the domestic and foreign production of ICT goods and services.

A particular feature of the Finnish recent history has been the rise and fall of the domestic ICT cluster. During the current crisis, the Finnish economy experienced a large structural shock when the positive effect of Nokia diminished after 2007. Through the lens of our model, the role of Nokia comes through large R&D investments, strong positive income effects, and rapid productivity growth in the ICT sector. In the model, the role of the Nokia shock can be studied by analyzing the effect of the strong total-factor productivity growth at the early 2000s, and the subsequent return of the productivity growth to the longer-term trend. The shock is calibrated to the model in a manner that generates a corresponding fall in the export shares of the ICT goods and services.

Another key structural growth factor in Finland are the (expected) changes in the supply of labor and demographics. The supply of labor is expected to decline over the next decades as a result of the aging of the population and low fertility rates, and this pattern will affect economic growth in several ways. First, it will govern the number of working hours in the economy. It results in a decrease of the production capacity, and for a reasonable substitution elasticity of labor and capital, there is also less need for investments. The expected amount of population and working hours also affects the aggregate consumption and the saving behavior.[17]

In the model, the forecasts for future population and labor supply is based on the forecasts of Statistics Finland (total population and the working aged population) until 2059, and the European Commission’s potential total hours forecast until 2022. The potential total hours are expected to follow the amount of working aged population after 2022. In this respect, we study how the recent downward revision of the employment growth in the 2018 Finnish population forecasts will affect economic growth.

In addition to taking into account the external drivers of growth, the model endogenizes several important patterns of structural change. First, the economic growth is accompanied by the increasing role of the traditional service sector in which productivity growth is slow. The low productivity growth results above all from the fact that a large bulk of the traditional services are personal, and thus applying the new technology in their production is difficult.

Due to the existence of the sectoral differences, the economic growth in the information era is unbalanced. It consists simultaneously of growth in sectors with low productivity growth, and sectors that can make huge productivity leaps by taking advantage of the ongoing digitalization and automatization. This has direct implications for the macroeconomic growth. The different sectors have to compete for the same inputs, especially labor, and the rapid productivity growth in some sectors tend to increase the overall input costs also in others.

17 It is possible that the ageing could change the sectoral patterns of consumption, for example by increasing the role of services of the old-age persons. However, there is no clear evidence of such patterns. Furthermore, it may differentiate the saving patterns of different age cohorts. In the current approach, however, there is a representative household implying that the welfare connections between different generations are assumed to be strong.

The unbalanced growth will result in more rapid increase of the product prices in the low productivity sectors, especially in the traditional service sector. As the final consumption of the services tends to be price inelastic – which means that they will be consumed despite their relative price increases – the share of the service sector in total value of production increases over time. Moreover, the structural change tends to shift resources to maintain production in sectors that have low productivity.

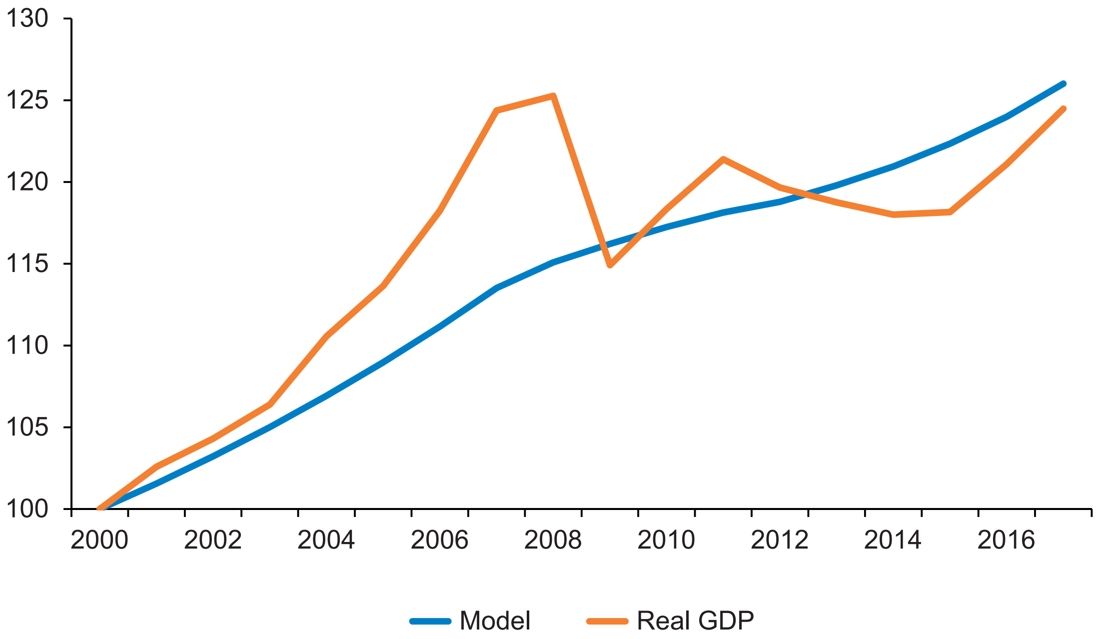
As a result, the aggregate productivity growth rate may start to decline. This ominous prediction of Baumol (1967) has received support in more recent research. In Ngai and Pissarides's (2007) paper differences in technological progress drive structural change. Acemoglu and Guerrieri (2008) analyze how sectorial differences in factor shares and capital deepening can lead to structural change. On the other hand, the prediction does not necessarily hold, if the sectors are tightly interlinked (Oulton, 2001). Recent work on the role of ICT in this framework includes that of Bakhshi and Larsen (2001) and Martinez et al. (2010).

Finally, we analyze the economic growth in a small open economy model that takes into account the changing comparative advantage between sectors and countries, especially the varying share of high-tech goods and services in exports.

4.2 Results

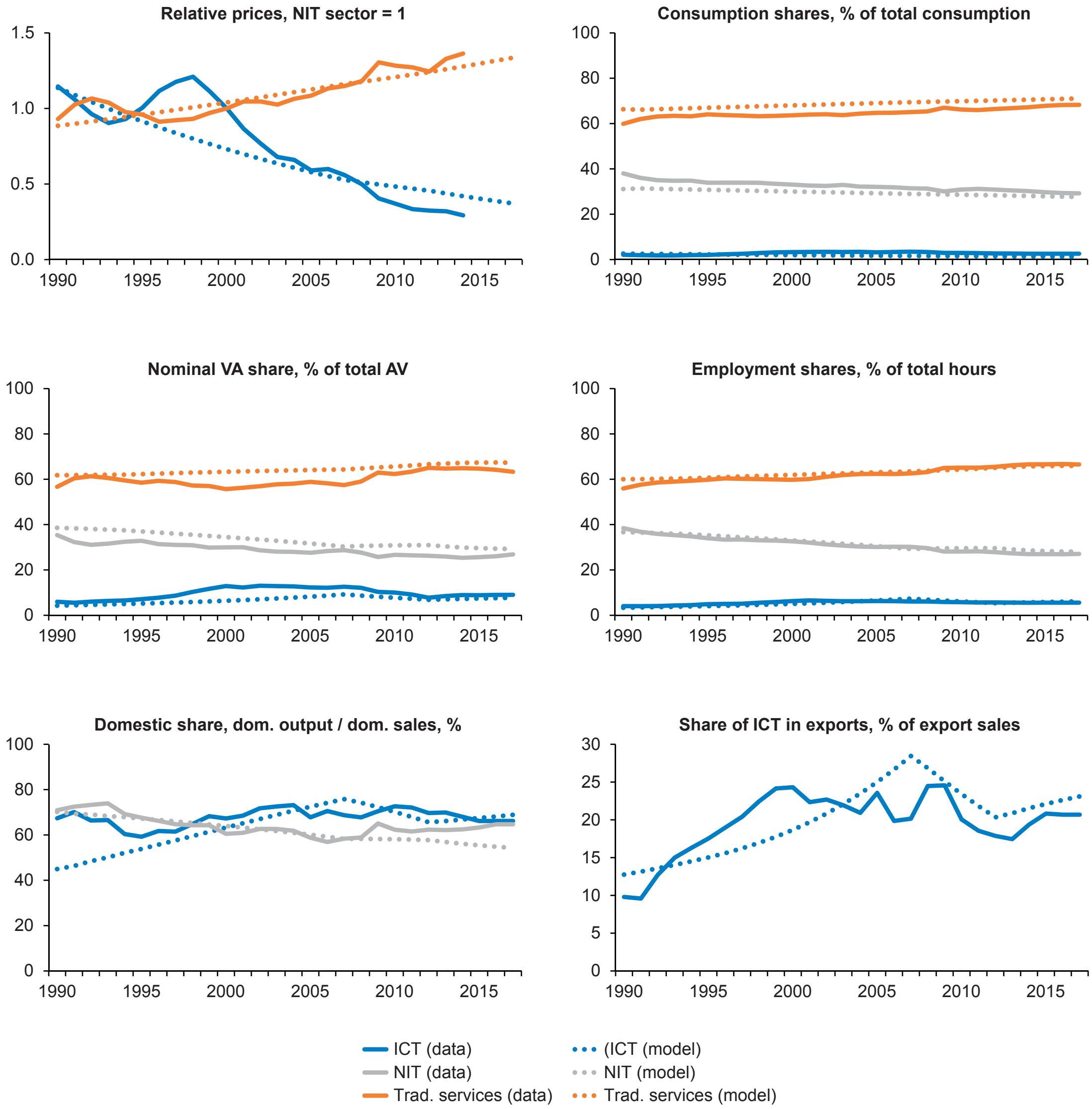
We start the analysis by reporting the behavior of the model in the years 2000 to 2017 and use it to assess our model performance. Figure 4.2 shows the baseline growth path of the model and compares it to the actual GDP volume growth in these years 2000 to 2017. The figure suggests that the baseline growth path matches rather well with the aggregate volume growth of the Finnish economy. Thus, it can be expected to provide a reasonable potential path of the economy also in the near future. Furthermore, Figure 4.3 reports the key struc-

Figure 4.2 The baseline growth path of the multi-sector model and the actual real GDP growth (2000 = 100)



tural changes of the macroeconomic variables. It shows that the model replicates dynamics concerning (1) the relative prices of the sectors, (2) the consumption shares of the sectors, the production shares of the three sectors, (3) the value added shares of the sectors, (4) the employment shares of the sectors, (5) the domestic content of the domestic final good, and (6) the share of ICT goods and services of the total exports. All in all, given that the model fits relatively well to the structural changes, we are fairly confident in using its projections to forecast GDP volume growth also in the medium-term.

Figure 4.3 The key structural changes of macroeconomic variables in the model vs. the data



The relative prices are the prices of a sector's consumption aggregate as relative to the price of the consumption aggregate of the traditional manufacturing sector. The consumption shares are the sectoral nominal share of the total consumption. The employment shares are the sectoral share of the total working hours. The domestic shares are defined as the value of the domestic production as relative to the total value of the domestic demand. The share of ICT in total exports is the share ICT goods and services in the total exports.

Sources: OECD, Statistics Finland, and own calculations.

We find that the forecasted average growth rate of the model's GDP volume growth is at 1.5% per annum in the years 2019–2023. The number is the same as Kotilainen (2015) has estimated to be the potential output growth rate for Finland in the middle run. This is also close to the growth rate estimated by the Ministry of Finance of Finland, see Kuismanen et al. (2015), or the European Commission (2018B).

While this growth rate provides our baseline forecast in the medium term, we next further analyze the anatomy of the growth. In particular, we use the quantitative model and counterfactual experiments to analyze the origins of the observed economic growth of the Finnish economy (Table 4.1).

We start by measuring the impact of the ICT on the aggregate economic growth. We estimate the effect of ICT by setting the productivity growth rate of the ICT sector, as well as the relative price change in the foreign ICT sector as equal to the corresponding growth rates in the traditional manufacturing (NIT). Comparing counterfactual scenarios with and without ICT shows that removing all ICT-specific technological change declines economic growth on average by -1.23 pps.

Thus, it seems that the ICT has a dominant role in the economic growth. The result is in line with Jalava and Pohjola (2008) who finds that ICT has a major importance for economic growth in Finland. The results are also comparable to the estimates-based general equilibrium models. Based on variants of the Greenwood et al. (1997) model, Bakhshi and Larsen (2008) find that in the UK, ICT investment-specific technological progress makes a significant contribution to productivity growth along the balanced growth path. Martinez et al. (2010) finds similar results in case of ICT during the period 1980–2005 in the U.S. It is notable, however, that this paper finds that the estimates for Finland are even larger than in the earlier international findings.

Table 4.1 The estimated average growth rate of the economy at the baseline growth path in 2018–2023

Scenario	Growth / effect on growth 18-23
Baseline average growth rate 2018–2023	1.48 %
Effect of 2015 vs. 2018 pop. forecast	-0.07 pps
Remaining Nokia shock effect	-0.07 pps
Effect of Baumol disease	-0.10 pps
Effect of ICT	+1.23 pps
Effect of trade openness	+0.53 pps

The table also contains the estimated effects of the counterfactual scenarios on the economic growth. The "Effect of 2015 vs. 2018 pop. forecast" scenario compares the differences of the growth rates with the 2018 population forecast by the Statistics Finland and the corresponding 2015 vintage. The "Remaining Nokia shock effect" compares scenarios with and without the Nokia boom-bust cycle. The "Effect of Baumol disease" scenario measures the difference in growth rates of the model when the consumption function is a Cobb-Douglas with constant factor shares, and the baseline CES with price inelastic intratemporal substitution elasticity. The "Effect of ICT" scenario compares the baseline and a scenario in which the productivity growth rate of the ICT sector, as well as the relative price change in the foreign ICT sector are equal to the corresponding growth rates in the traditional manufacturing (NIT). The "Effect of trade openness" scenario compares the baseline and a scenario in which the economy is effectively closed.

While the ICT sector in Finland has been subjected to major volatility in the recent years, we find that during the time interval 2019–2023 the effect of the Nokia shock on the economic growth has mostly died out. While the collapse of the production generates a roughly 5 percent decline in the baseline path after the 2007, as compared to the previous GDP volume trend, the growth rate of the economy is only -0.07 percentage points weaker in 2019–2023 because of the collapse. The latter finding is made by comparing the growth rates of simulation without the Nokia boom-bust cycle, and with it.

In the previous subchapter, we referred to a literature pioneered by Baumol (1967) suggesting that productivity differentials across sectors can affect the economic growth. Service sector with low productivity growth has to compete for the same inputs, especially labor, with more progressive sectors which will cause their product prices to rise relative to the overall price level. If final consumption is price inelastic, the structural change shifts resources towards maintaining production in sectors with low productivity, and decreases the aggregate productivity growth rate over time.

The effect of the Baumol's disease can be governed in the model by adjusting the intratemporal price elasticity of substitution across sectoral consumption. When the intratemporal substitution elasticity is below 1 (the demand is price inelastic), changes in the consumption respond to increase in the relative price of services by shifting the production resources of the economy towards supporting the production of services. In the Finnish case, the consumption data between the years 1991 and 2011 suggests that the price elasticity (between NIT and S) could be close to 0.5. The effect of the Baumol's disease can be effectively removed by setting the elasticity to a number very close to 1 in which case the consumption shares of the different sectors remain close to constant. Thus, the alteration of the elasticity provides a natural way to estimate the impact of the Baumol's disease.

We find that the unbalanced growth decreases the growth rate of the economy, but the effect is rather small, the growth rate falls by -0.10 pps due to the changes in the consumption patterns. Moreover, the Baumol's disease does not appear to lead to a declining rate of aggregate growth. With the Finnish example, it confirms that if technology progresses in sectors predominantly devoted in production of investment or intermediate goods, the economy can expand without the consumption patterns affecting the long-run aggregate growth rate of the economy, as in Greenwood et al. (1997), Oulton (2001), and Ngai and Samaniego (2009). Furthermore, in line with Matsuyama (2009) and Yi and Zhang (2010), the paper finds that in a Ricardian model of trade, high manufacturing productivity growth does not necessarily lead to a decline in manufacturing employment in an open economy.

As regards to the economic openness, we find that it has utmost importance in determining growth. When the economy is effectively closed after substantially increasing the cost of trade, and thereby reducing the size of economic growth to 1 percent of the original, the growth rate of the economy falls by 0.53 pps. The estimate is large, but still conservative, as the scenario assumes that the total-factor productivity growth can remain as fast as before in the domestic sectors. Thus it still implies that there are technological spillovers across countries. Another mentionable feature is that in the closed model the GDP volume grows at a significantly lower growth path than in the baseline.

Finally, we have investigated the role of the recent revisions of the Statistics Finland population forecasts between the 2015 to the 2018 vintages. While our model uses the potential hour growth based on the spring 2018 Commission forecast that are not affected by the recent revision, we note that the population forecasts and the potential hours estimates after 2022 are revised downward. Due to these revisions, the long-term growth prospects concerning the aggregate demand and the labor input are lower, which affects the current potential output growth especially through lowered investments. As a result, we find that the potential growth rate of the model in the period 2019 to 2023 has fallen by 0.07 pps.

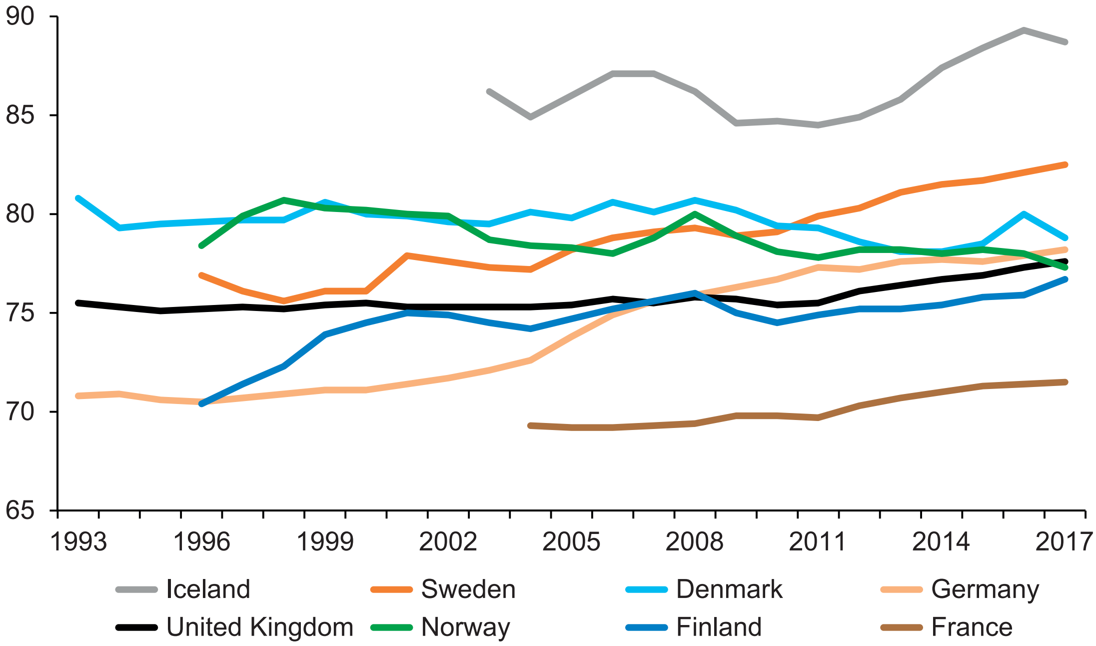
4.3 Understanding the growth potential requires alternative scenarios

Our prior analysis of the estimates of the labor and productivity potential suggests that they are frequently and heavily revised. Therefore, our recommendation is also to consider alternative scenarios that may be possible, but are not analyzed with similar, model-based scrutiny, as our baseline. Rather, we build the discussion of alternative scenarios in this subsection on the recent analysis by Kaitila et al. (2018).

In this respect, we first discuss the potential for improvements in the labor input. As was shown in the analysis in Section 2.3., the current participation rate in Finland is probably close to its potential level. However, if we compare the participation rate in Finland to that in a few reference countries, it can be observed that there is still room for improvement in the participation rate of labor market in Finland (see Figure 4.4). For instance, the rate of participation in Germany or Denmark should not be a too ambitious objective for Finland. This would demand well-planned structural reforms that increase the potential participation rate.

Kaitila et al. (2018) argue that, with help of structural reforms, the participation rate in the Finnish labor market could potentially rise to the same level as, on average, in a following

Figure 4.4 Participation rate in selected European countries (15–64 years old population)



Source: Eurostat.

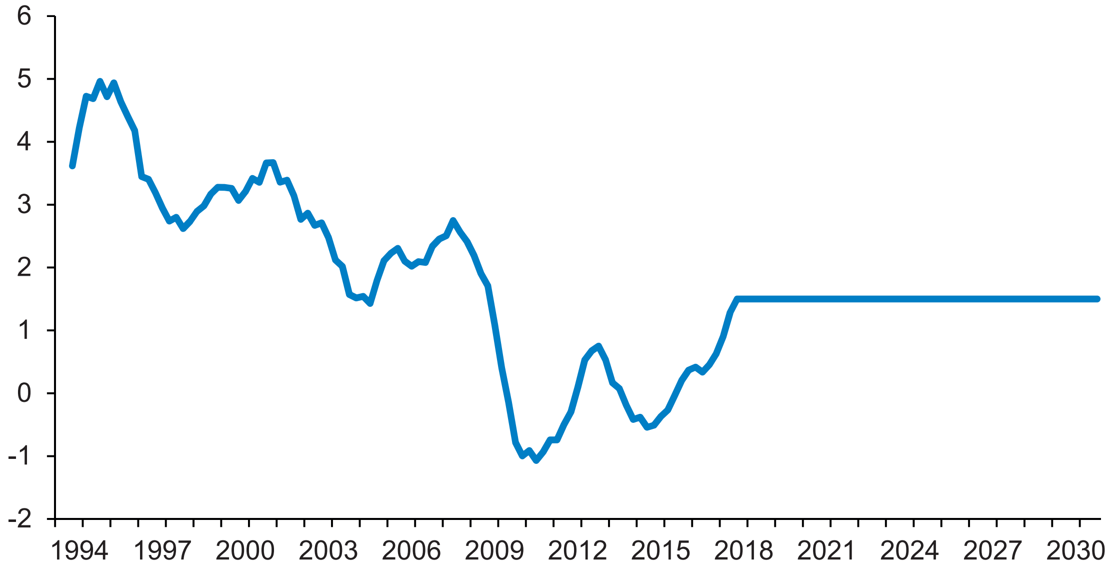
reference group of countries: Sweden, Germany, Denmark, and Norway. In this scenario the labor input, adjusted by demography (the rising share of people aged over 64 years) and a presumed increase in the share of part-time workers, could rise by 0.4 per cent a year between 2019 and 2023. The scenario also assumes that the Finnish unemployment rate would decrease, approximately, to an average level observed in this group of four reference countries, with the unemployment rate calculated separately in each age group in order to capture the differences in demography.

As it has been previously argued by this study and others (Kotilainen, 2015; Kuismanen et al., 2015; European Commission, 2018B), these assessments are based on estimations of labor productivity growth and, the official population forecast calculated by the Statistics Finland which basically shows no working-age population increase for Finland in the 2020s. Thus, irrespective of potential changes in participation rate with help of structural reforms, a great deal of the potential output growth for Finland in the next decade will come from increases in labor productivity.

However, for the 1.5 per cent productivity growth per year to actualize, the labor productivity growth needs to accelerate from the recent decade's relatively low pace. On the other hand, the labor productivity growth rate of 1.5 per cent a year would be much lower than the growth rate seen, for instance, in the 1990s. Figure 4.5 depicts the historical development of labor productivity (an annual growth in the real value added divided by labor hours) at aggregate economy level using a three year's moving average of seasonally adjusted quarterly national accounts data and the forecasted 1.5 per cent annual growth for years 2018–2030.

Kaitila et al. (2018) assess that a "realistic" productivity growth for Finland could be 1.7 per cent a year in the near future, that is between years 2019 and 2023. The estimation is based on analysis of the latest available data on productivity developments in the most important sectors for the Finnish economy. Specifically, the analysis intends to understand the recent

Figure 4.5 Labor productivity growth, actualized in 1990–2017 and forecasts for 2018–2030



Source: Statistics Finland.

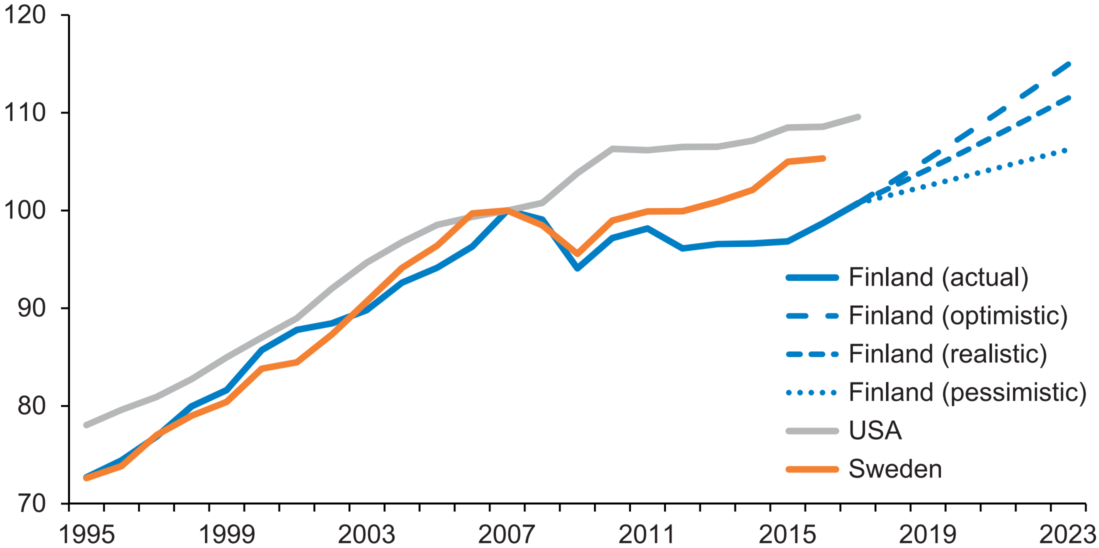
changes in productivities in private services and industrial sector, and extrapolates the development forward using the implications provided by the data.

For instance, the scenario assumes that productivity growth in private services would accelerate by 0.5 percentage points next year, and this higher rate of growth would continue until 2023. This would convert into 2.4 per cent productivity growth in private services. The scenario also assumes that industrial sector productivity in Finland would be in line with the US average on that sector between 2005–2016. This would convert into 1.8 per cent productivity growth for the industrial sector in Finland. The development of labor productivity implied by this scenario is illustrated in Figure 4.6.

In addition to this baseline scenario, Kaitila et al. (2018) produce a “pessimistic” and an “optimistic” scenario for the productivity development for Finland for 2019–2023. The pessimistic scenario assumes that Finnish productivity growth in these years would equal to the US average productivity growth at the aggregate economy level in the period 2005–2016, converting into a 0.9 per cent labor productivity growth for Finland. The optimistic scenario, instead, assumes that a yearly productivity growth in Finland would rise to 2.2 per cent for the period 2019–2023.

All in all, the potential output growth between 1 and 1.7 per cent in the middle run can be achieved with the current structures of the Finnish economy. Yet even that pace assumes that there will be a slight upward turn in labor productivity as compared to its trend after the financial crisis. In a positive scenario, appropriate structural reforms targeted at the potential participation rate could raise the potential output growth to 1.7–2.1 per cent a year in the middle run. In the long run, however, the potential output growth in Finland will be weighed down by a weak demography driven by increasing share of pensioners in population combined with a low fertility rate that seems to be on a downward trend according to the latest estimates by the Statistics Finland.

Figure 4.6 Productivity scenarios for Finland



Sources: Statistics Finland, OECD (STAN Database) and calculations by Mika Maliranta, for details, see Kaitila et al. (2018).

4.4 Concluding remarks on the medium-term production potential

In this section, we discuss the medium-term growth potential of the Finnish Economy in the years 2019–2023 by using structural macroeconomic modelling. In particular, we make use of a multi-sector neoclassical growth model that incorporates forecasts of total-factor productivity changes, resources of the economy, as well as the conditions for external trade into a coherent forecast of the economic growth. In Figure 25 we show that the baseline growth path of the model and its structural changes are rather well matched with the data in the years from 2000 to 2017, and therefore, we are fairly confident in using its projections to forecast GDP volume growth also in the medium-term.

We find that the average GDP growth rate produced by the model forecast GDP is 1.5% per annum for the years 2019–2023, when the model is employed with the long-term historical average total-factor productivity growth in different sectors, the latest population forecasts, as well as the external market that matches with the actual shares of foreign imports in the domestic markets and the structure of the Finnish exports. By using counterfactual scenarios, we find that the economic growth is predominately determined by the technological improvements in the information and communications technology and the external trade.

Our prior analysis of the estimates of the labor and productivity potential suggests that they are frequently and heavily revised, and thus we also discuss alternative scenarios. We discuss the growth potential using a scenario in which the Finnish economy reaches the labor market outcomes of the neighboring countries, or the economy experiences productivity growth that differs from the baseline. According to our analysis, the potential output growth between 1 and 1.7 per cent in the middle run can be achieved with the current structures of the Finnish economy. In a positive scenario, appropriate structural reforms targeted at the potential participation rate could raise the potential output growth to 1.7–2.1 per cent a year in the middle run. In the long run, however, the potential output growth in Finland will be weighed down by a weak demography driven by increasing share of pensioners in population combined with a low fertility rate that seems to be on a downward trend according to the latest estimates by the Statistics Finland.

5 CONCLUSIONS

This project has developed the methodology for measuring the potential output and assessing the medium-term growth prospects for the Finnish economy by forecasting its potential. We base our measurement of the potential output on the production function method that is currently used by most economic institutions (OECD, IMF, European Commission). It will enable the use of research data on production technology and the behaviour of different production factors in assessment of the potential. The idea is to use an overall concept of economic production capacity (potential production function) based on observations on the state of the various components of the production function.

Our starting point is the method of the European Commission because of its important economic policy role. The aim of the project is to improve the production function method in order to better predict the potential and production gap in real time and construct it to be more suitable for the Finnish economy. The method used by the European Commission raises a number of problems, and this project addresses a few remedies that aim to improve its functioning. In particular, we apply novel approaches to the estimation of the Finnish production function (constant elasticity of substitution, CES) and the potential output (Sequential Monte Carlo method, SMC) with the aim of improving the method.

We use a more general form of the production function (CES) than the Cobb-Douglas production function that is used by the EC. We show that the Cobb-Douglas specification of the production function can be clearly rejected. The distinction between labor augmenting productivity and capital augmenting productivity that arises from the CES model matters for the measurement of the production potential, especially the potential component of the total-factor productivity (TFP). The capital augmenting productivity tends to develop in a more procyclical manner than the labor augmenting productivity; a result that holds true both when we use the commission's output gap method and when we jointly estimate the potentials with our SMC estimator.

Furthermore, we apply the SMC method to jointly estimate NAWRU and the potential level of labor force participation rate. We find that the potentials are similar to the EC estimates during the Great Recession, but considerably smoother during the Finnish Great Depression of the 1990s. Our findings provide evidence against large and short-lived variation of the potential labor input during economic crises. We find that especially the NAWRU and the labor augmenting efficiency are very sensitive to the real-time uncertainty.

We also study the medium-term growth potential of the Finnish Economy in the years 2019–2023 by using Etla's multi-sector growth model. We find that the average GDP growth produced by the model forecast is 1.5% per annum in the years 2019–2023 under the expected long-term trends in technology, demography, and trade. According to the model, the economic growth is predominately determined by the technological improvements in the information and communications technology and the external trade.

APPENDIX TO SECTION 2

Note: The numbering of equations refers to Section 2.

Below the index t ranges both over the points of time $t = 1,...,T$ for which observations are actually available and the point of normalization $t = 0$, when not stated otherwise. Putting $X = X_0$, $K = K_0$, $B = B_0$, $L = L_0$, the formula (7) immediately implies that

$$F(X_0, K_0, B_0, L_0) = Y_0$$

so that for all t, the output Y is given by

$$Y_t = F(X_t, K_t, B_t, L_t)$$

Further, we now conclude that

$$\frac{\partial Y}{\partial K} = \left[\pi_0 \left(\frac{X}{X_0 K_0}\right)^{-\rho} K^{-\rho-1}\right] Y_0 \left[\pi_0 \left(\frac{X}{X_0}\frac{K}{K_0}\right)^{-\rho} + (1-\pi_0)\left(\frac{B}{B_0}\frac{L}{L_0}\right)^{-\rho}\right]^{-(1+\rho)/\rho}$$
$$= \left[\pi_0 \left(\frac{X}{X_0 K_0}\right)^{-\rho} K^{-\rho-1}\right] \frac{Y^{1+\rho}}{Y_0^{\rho}}$$

so that

(31) $$\frac{K_t}{Y_t}\left(\frac{\partial Y}{\partial K}\right)_t = \left[\pi_0 \left(\frac{X_t K_t}{X_0 K_0}\right)^{-\rho}\right]\left(\frac{Y_t}{Y_0}\right)^{\rho}$$

and that, similarly,

(32) $$\frac{L_t}{Y_t}\left(\frac{\partial Y}{\partial L}\right)_t = \left[(1-\pi_0)\left(\frac{B_t L_t}{B_0 L_0}\right)^{-\rho}\right]\left(\frac{Y_t}{Y_0}\right)^{\rho}$$

Our two last results imply that

(33) $$\frac{K_t}{Y_t}\left(\frac{\partial Y}{\partial K}\right)_t + \frac{L_t}{Y_t}\left(\frac{\partial Y}{\partial L}\right)_t = \left[\frac{Y_t}{Y_0}\right]^{-\rho}\left(\frac{Y_t}{Y_0}\right)^{\rho} = 1$$

i.e. that it is possible to divide the output between labor and capital so that they both get their marginal products. For each $t = 1,...,T$ we let π_t denote the output share of capital in this case. In other words, we put

(34) $$\pi_t = \frac{K_t}{Y_t}\left(\frac{\partial Y}{\partial K}\right)_t$$

and observe that, according to (31)

$$\frac{(\partial Y/\partial K)_0 K_0}{Y_0} = \pi_0$$

so that (34) remains valid also when $t = 0$ and π_0 has its previous implicit definition (7).

Letting t range over t = 1,...,T, letting $\overline{\pi}$ denote the geometric mean of π_t, and forming the geometric mean of the corresponding formulas (31), one may conclude from (34), (31), and (10) that

$$\overline{\pi} = \pi_0 \zeta^{-\rho}$$

which is equivalent with (11).

Similarly, we may conclude from (32), (33) and (34) that

$$1-\pi_t = \frac{L_t}{Y_t}\left(\frac{\partial Y}{\partial L}\right)_t = \left[(1-\pi_0)\left(\frac{B_t L_t}{B_0 L_0}\right)^{-\rho}\right]\left(\frac{Y_t}{Y_0}\right)^{\rho}$$

and taking the geometric mean of both side when t range over t = 1,...,T, that

$$\overline{1-\pi} = (1-\pi_0)\zeta^{-\rho} = \zeta^{-\rho} - \overline{\pi}$$

which is identical with (12). We may now solve ζ as

$$\zeta = \left(\overline{1-\pi} + \overline{\pi}\right)^{\rho}$$

Finally, we turn to the task of proving (17). Shifting attention to the case in which (14) and (15) are valid, we first conclude from (14), (15), (31), and (32) that

$$\frac{r_t K_t}{w_t L_t} = \frac{(\partial Y/\partial K)_t K_t}{(\partial Y/\partial L)_t L_t} = \frac{\pi_0}{1-\pi_0}\left(\frac{K_t / L_t}{K_0 / L_0}\right)^{-\rho}\left(\frac{X_t/B_t}{X_0/B_0}\right)^{-\rho}$$

In a next step, we remember that by assumption $K_0 = \overline{K}$, $L_0 = \overline{L}$, $X_0 = \overline{X}$ and $B_0 = \overline{B}$, and that $\pi_0 = \zeta^{\rho}\overline{\pi}$ according to (11). Taking logarithms, it now follows that

$$\ln\frac{r_t K_t}{w_t L_t} = \ln\frac{\overline{\pi}}{\zeta^{-\rho} - \overline{\pi}} - \rho \ln\frac{K_t / L_t}{\overline{K} / \overline{L}} - \rho \ln\frac{R_t}{\overline{R}}$$

APPENDIX TO SECTION 3: METHODOLOGY

Kalman filter

This paper uses a standard Kalman filter to provide a likelihood for the data under a given vector of model parameters. The paper initiates the estimator by using a diffuse Kalman filter, when the state variables are expected to be non-stationary. Furthermore, the paper uses a backward filtration of the state variables. (see, e.g., Durbin & Koopman, 2012; Planas & Rossi, 2014)

Sequential Monte Carlo

The SMC algorithm that we use is based on the Herbs and Schorfheide (2016). To characterize the posterior probability distribution, the method resorts to the notion of particles. A particle i is a pair of a parameter value and its probability (θ^i, p^i). The probability distribution is characterized by a large number (N) of particles.

We start by introducing the idea of the importance sampling. Let us denote the posterior density of the parameter vector by $\pi(\theta)$. Estimation of the distribution consisting of $\pi(\theta)$ is the goal of our exercise. In particular, by using the Bayes' rule, the posterior probability can be denoted as

$$\pi(\theta) = \frac{p(Y|\theta)p(\theta)}{p(Y)} = \frac{f(\theta)}{\int f(\theta)d\theta},$$

where $p(\theta)$ is the prior density, $p(Y|\theta)$ is the conditional density of the data conditional on the parameter value, and $p(Y)$ is a normalization term that is potentially needed to ensure that the integral of the densities is 1. It should be noted that $\pi(\theta)$ does not have a general closed-form solution and samples from the distribution has to be taken by resorting to numerical methods.

We can start thinking about the importance sampling by assuming that there is a different, tractable density $g(\theta)$ that we can sample from to approximate $\pi(\theta)$. For the sake of argument, let us for now assume that $f(\theta)$ is observed.

For a function of the parameters, $h(\theta)$, the importance sampling is based on the identity

$$E_\pi[h(\theta)] = \int h(\theta)\pi(\theta)d\theta = \frac{\int h(\theta)\frac{f(\theta)}{g(\theta)}g(\theta)d\theta}{\int \frac{f(\theta)}{g(\theta)}g(\theta)d\theta}$$

The ratio $w(\theta) = f(\theta) / g(\theta)$ is called the (unnormalized) importance weights. For i = 1 *to N*, one can draw $\theta^i \sim g(\theta)$, and compute the unnormalized and normalized importance weights (W^i):

$$w^i = w(\theta^i) = \frac{f(\theta^i)}{g(\theta^i)}, W^i = \frac{w^i}{\frac{1}{N}\sum_{i=1}^N w^i}$$

Finally, an approximation of the expected value of the function, $E_{\pi}[h(\theta)]$, is

$$\bar{h}_N = \frac{1}{N}\sum_{i=1}^{N} W^i h(\theta^i)$$

It is worth noticing that the distribution of the unnormalized importance weights depends on the accuracy of the approximate distribution. If the accuracy is low, there tends to be large values of w^i representing parameter values that have low $g(\theta)$ but high $f(\theta)$. On the other hand, when the distributions are equal, the weights are all 1.

In practice, the success of the method hinges on the quality of the proposed density g. If it happens to perfectly match $\pi(\theta)$ the approximation equals the true expected value. That is seldomly the case. Rather, the key to use the method is to provide gradually improving estimates.

The idea of the SMC is to iteratively adjust the positions and probabilities of the individual particles in order to ultimately correctly specify the posterior distribution of the parameter. The iterative process is started with an initial guess for the distribution, denoted in Figure 3.1 by θ_0 that is based on the information concerning the prior distribution. In each round of the iteration, steps are taken to use the previous guess as a basis of a new, improved guess about the posterior distribution. More weight is gradually given on the approximated posterior density. Ultimately, under certain conditions, the approximation converges to the actual posterior density by the last iteration that we denote by θ_M.

During each round of the iteration, the characteristics of the particles are updated in three steps. The first step adjusts the weights of the particles, the second step resamples the particles, and the third step propagates the obtained particles via a Markov Chain Monte Carlo algorithm.

- C: The correction step increases the weight given to the approximated posterior distribution, and correspondingly reweights the particles from the previous stage. The step provides the so-called incremental weights and their normalizations that are used to create importance sampling approximation of the new posterior distribution.

- R: Resamples from the new posterior distribution with the aim to re-characterize the distribution with more equalized particle weights and thereby to increase accuracy of subsequent importance sampling approximations.

- S: Propagate the obtained particles via a Markov Chain Monte Carlo algorithm with a transition density obtained from the particles of the previous step in order to provide the iteration's final proposal density for the posterior.

Test statistics

We use a few test statistics in order to ensure that the estimation procedure functions correctly. First, we control for the concentration of the unnormalized weights. To motivate the statistics, we note that the central limit theorem suggests that the distribution of the approximation is

$$\sqrt{N}(\bar{h}_N - E_{\pi}[h(\theta)]) \rightarrow N(0, \Omega(\mathrm{h}))$$

where the variance term Ω(h) can be shown to be crudely approximated by the sample variance of i.i.d. draws from the posterior distribution of h, V_π [h], and the sample variance of π / g under i.i.d. draws from g, $V_g[\pi / g]$,

$$\Omega(h) \approx V_\pi[h](1 + V_g\left[\frac{\pi}{g}\right])$$

The approximation highlights that the larger the variance of the importance weights, the less accurate the Monte Carlo approximation relative to the accuracy that could be achieved with an iid sample from the posterior. A useful test statistic arises from the ratio of the variance of the sample from the true posterior, and the variance of the approximation. The ratio can be approximated by:

$$Ineff = \frac{V_\pi[h]}{\Omega(h)} \approx \frac{1}{1 + V_g\left[\frac{\pi}{g}\right]}$$

A natural corollary is to report the efficient sample size (ESS), i.e. the sample size transformed into units of iid draws from the true distribution:

$$ESS = \frac{N}{1 + V_g\left[\frac{\pi}{g}\right]}$$

It is noticeable that when the ESS falls below a certain level that triggers a resampling in which the algorithm draws new particles and equalizes the distribution of the particles.

As a part of the approximation, we use a standard Metropolis Hastings algorithm. While we omit the full description of the model, we note that we keep track of the acceptance rate of the MH algorithm's functioning. The acceptance rate reports the probability of the algorithm to accept a new parameter value from the candidate distribution. The acceptance rate should not be too high nor too low. If the acceptance rate is too high, the lack of persistence of the draws makes the estimates noisy and unstable. On the other hand, too low acceptance rate indicates that the algorithm is stuck, and do not converge towards the correct parameter value.

APPENDIX TO SECTION 3: SMOOTHED STATES

Estimates of the potential labor input

Figure A3.1 Smoothed potential state estimates (Unemployment and trend estimates, % of labor participants)

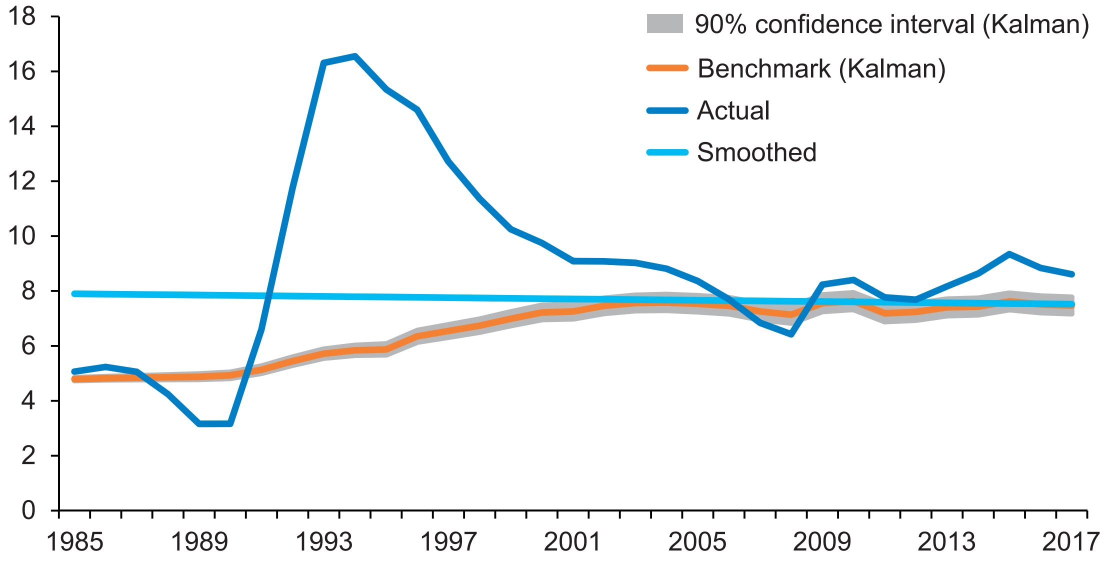
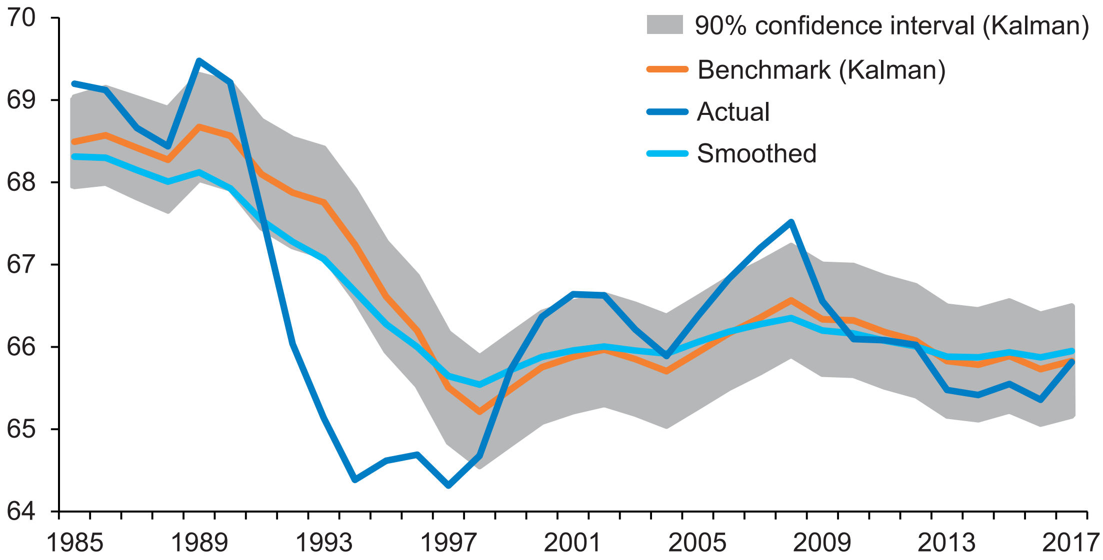


Figure A3.2 Smoothed potential state estimates (Participation rate and trend, % of working aged population)



Estimates of the potential factor efficiencies

Figure A3.3 Smoothed potential state estimates, the capital-augmenting productivity, log-scale

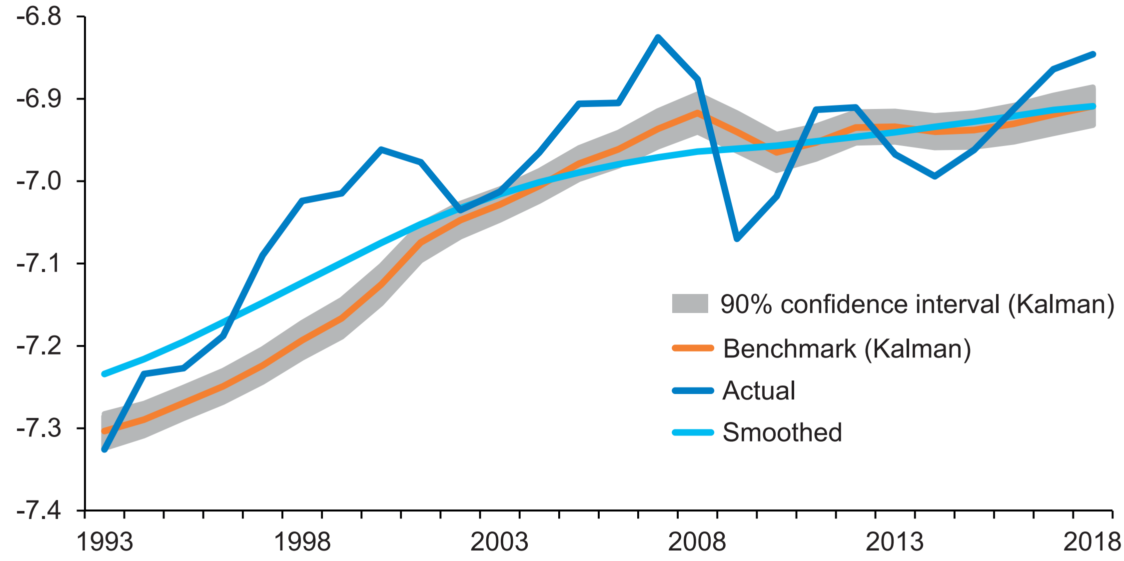
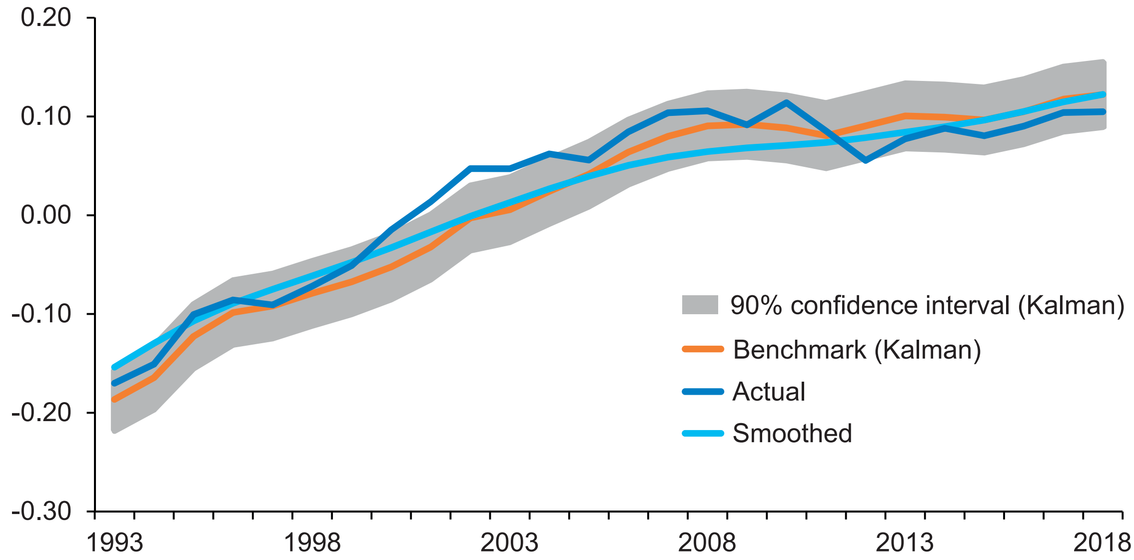


Figure A3.4 Smoothed potential state estimates, the labor-augmenting productivity, log-scale



APPENDIX TO SECTION 4

A technical introduction to the model

The considered model consists of sectors producing ICT, traditional goods, and traditional services.[18] The production side of the economy closely resembles Ngai and Samaniego's (2009) version of the investment-specific technological change model. In the model, each sector has a unique Cobb-Douglas production function with industry-specific factor intensity shares and multi-factor productivity terms, which are calibrated using the National Accounts. The sectors produce sector-specific intermediate and capital goods, the difference being that intermediate goods have to be used during the period of its production. There are two capital stocks based on ICT and traditional goods.

Unlike Ngai and Samaniego (2009), the model allows structural changes in consumption. The representative household is assumed to consume sector-specific goods according to a CES aggregator with intratemporal elasticity strictly lower than 1. This relates the model to the recent papers by Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008). The model differs from Acemoglu and Guerrieri (2008) by assuming that changing relative prices affect the composition of production inputs and final consumption differently, a case considered by Ngai and Pissarides (2007). The unit elasticity of substitution of production functions reflects the fact that nominal factor shares remain stable over time in input-output tables. The intratemporal elasticity of substitution is based on the relationship between nominal consumption patterns and relative prices of consumption goods.

Furthermore, the considered economy is open to capturing changing comparative advantage between sectors and countries, especially the increasing share of high-tech goods and services in exports of advanced countries. Modeling international trade is based on Uy et al. (2013), who considers a version of Ngai and Pissarides (2007) in an open economy. Tradable sectors consist of heterogeneous firms and sector-specific goods are composites of firm-level goods produced either in a domestic country or abroad. Domestic, sector-specific production functions are aggregates over the firm-level production functions, which are identical up to the MFP term. Distribution of firm-level MFP terms follows the assumptions in the Eaton and Kortum (2002) model of international trade, which makes it easy to estimate unit costs of foreign countries and trade barriers. Unlike in Uy (2010), the size of the foreign market and unit costs abroad are taken to be exogenous.

Firms

In the open sectors (ICT- goods and services production (ICT), and traditional industry and construction (NIT)) the sectors domestic final good is a combination of domestic goods and services and imported goods and services. The closed service sector (S) directly provides domestic final goods. The open sectors produce investment goods, intermediate goods, and consumption goods. The investment goods are assembled to the total productive capital stocks of the economy. There are two stocks: NIT- and ICT-capital stocks. The service sector (S) provides intermediate goods and consumption goods for the domestic purposes.

18 ICT = ICT related manufacturing and services; traditional services = private and public services; traditional goods = other industries.

Each sector produces its goods by combining six different inputs (m_k) according to Cobb-Douglas production function (k = ICT-capital, NIT-capital, labor force, and S-, ICT- ja NIT-intermediate goods). The multi-factor productivity of a firm i is denoted as MFP_i. The multi-factor productivities are equal in the closed sector, but in the open sectors they vary across firms. The three sectors are competitive and the firms maximize their profits. In particular, the firms maximize the value of their production by adjusting the amounts of inputs given the prices of their final good and the sector-specific (denote sector by q) rental prices of inputs w_{kq}:[19]

$$\max\left[p_i * F_i - \sum_{k=1}^{6} w_{kq} * m_{ki}\right] = \max\left[p_i * MFP_i * \prod_{k=1}^{6} m_{ki}^{\alpha_{kq}} - \sum_{k=1}^{6} w_{kq} * m_{ki}\right],$$

where α_{kq} is the nominal factor share k in sector q. It is useful to describe the result of the optimization problem in terms of the unit cost function that defines the optimat unit cost of the firm i in sector q UC_{iq}:

$$\mathrm{UC_{iq}} = \frac{1}{A_i} \prod_{k=1}^{6} w_{kq}^{\alpha_{kq}},$$

where $A_i = MFP_i \prod_{k=1}^{6} \alpha_{kq}^{\alpha_{kq}}$ is the multi-factor productivity with additional factor-weight terms that arises from the optimization. In the model, the firms do not make excess profits, and thus the unit costs equal the unit price of the goods and services, $UC_i = p_i$.[20] The price of the intermediate goods is the same as the domestic final goods (combination of the domestic good and the intermediate good). The price of the intermediate goods is the same as the domestic final goods (combination of the domestic good and the intermediate good).

In order to model international trade, we use assumptions concerning the sectoral productivity that are similar to Uy et al. (2013). The closed, service sector produces homogenenous goods with identical production functions at the firm level. The competitiveness assumption implies that $UC_S = p_s$, and the optimality of the production that

$$\mathrm{UC_S} = \frac{1}{A_S} \prod_{k=1}^{6} w_{kS}^{\alpha_S}.$$

The tradable sectors sell differentiated goods. Let us denote the sectors by q = [NIT,ICT], and the individual firms receive an index value $i_q \in [0,1]$. Within sectors, the firms are otherwise identical, but the total-factor productivities may differ. The firms may operate domestically or in other countries, and their products are combined symmetrically to domestic final goods:

$$F_q = \left(\int_0^1 F_{i_q}^{\eta_q}\, dz\right)^{\frac{1}{\eta_q}}$$

where $\eta_q < 1$ is the elasticity of substitution between the goods. Each individual good i_q is purchased from a country that provides it with the cheapest price, and it is imported to the purchasing country and used as a part of the domestic final good. The transportation involves a cost.

19 The rental costs can differ across sectors due to taxation.

20 In the closed sector, the price of the final good is equal for each firm, while in the open sector (with heterogeneous goods) there is enough firms for each good (with separate level of MFP) to push the excess profits to zero.

When the distribution of the total-factor productivities is assumed to exhibit the so-called Frechet-distribution that is a flexible functional form, and furthermore, it is assumed that the purchases are always made from the location that has the lowest price when the price of the shipping is included, the model yields simple functional expressions for the key trade equations. Eaton and Kortum (2002) show that the price of product q in country c is a function on the transportation costs and unit prices:

$$p_{qi} = \gamma \Phi_{qc}^{-\frac{1}{\theta_q}},$$

where $\Phi_{\mathrm{qc}} = \sum_{j=1}^{N} TC_{qcj}^{-\theta_q} UC_{qk}^{-\theta_q}$, TC_{qcj}, is product q transportation cost from country j to country c, and θ_q is a parameter that quantifies the importance of the relative advantage.

Similarly, the structure of the trade can be expressed as a function of the unit costs. Under the Frechet-distribution, the shares of the different countries c in the total demand in sector q in country j are

$$\pi_{qcj} = \frac{TC_{qcj}^{-\theta_q} UC_{qj}^{-\theta_q}}{\Phi_{\mathrm{qi}}}$$

The derivation of the expression can be found in Rodriquez-Clare (2007).

The households

A representative household earns labor income and receives rental income from capital. The household can save or consume its income. The household saves by investing in the sectoral investment goods (ICT or NIT) that are accumulate into the productive capital stocks of the economy.[21] The household maximizes the value of its consumption basket over time. The aggregate utility function exhibits a standard CRRA form, and the household weights each of its member (N_t) with an equal weight

$$V_s = \sum_{t=s}^{\infty} \beta^{t-s} N_t \frac{U(C_t)^{1-\rho} - 1}{1-\rho} - \xi_{St} L_{St} - \xi_{ITt} L_{ITt} - \xi_{NITt} L_{NITt}$$

so that the wage and the capital income, as well as the lump-sum capital tax returns equals the cost of investment, consumption, and the capital tax.

$$\sum_{i}^{S,ICT,NIT} w_t^{L_i} L_i + \sum_{q}^{S,ICT,NIT} \sum_{k}^{ICT,NIT} w_{K_k qt} K_{qkt} + T_t$$
$$= \sum_{q}^{S,ICT,NIT} p_{q,t} C_{q,t} + \sum_{q}^{ICT,NIT} p_{q,t} I_{i,t} + \sum_{q}^{S,ICT,NIT} \sum_{k}^{ICT,NIT} \tau_{K_k qt} w_{K_k qt} K_{qkt},$$

where $w_{K_k qt}$ denotes the capital k rental cost in sector q. Because the tax returns match with the collected taxes that for the sake of simplicity also involves the depreciation of the capital, the tax return, T_t, is

$$T_t = \sum_{q}^{S,ICT,NIT} \sum_{k}^{ICT,NIT} \tau_{K_k qt} w_{K_q kt} K_{qkt},$$

21 While the current version of the model omits investments in technology, in the previous work, Ali-Yrkkö et al. (2017), we have extended the model to include investments in R&D by using a variant of Acemoglu and Guerrieri (2008) endogenous growth model. While it is shown that the model can replicate the R&D behavior, it is notable that the model outcomes are similar.

where $\tau_{K_k qt}$ is the tax rate of capital k in sector q. The individual decision makers take the tax rate as given, and since the there is a lump-sum tax return, the tax has a distortive effect in the economy.

The labor input $L_t = L_s + L_{IT} + L_{NIT}$ is assumed to be exogenous, reflecting the independence of the long-run productivity growth and the labor supply decisions. The labor input is calibrated to match the potential hours of the economy. There are permanent wage differentials across the sectors. In the model, they are caused by differentiated disutility of work across sectors.

For a single member of the household, the utility function is of the CES form:

$$U(C_t) = \left(\omega_S \left(\frac{C_{St}}{N_t}\right)^{\frac{\epsilon-1}{\epsilon}} + \omega_{IT}\left(\frac{C_{ITt}}{N_t}\right)^{\frac{\epsilon-1}{\epsilon}} + \omega_{NIT}\left(\frac{C_{NITt}}{N_t}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}$$

The utility maximizing consumption basket fulfills the following optimality conditions (subindices i and j refer to all sectors, k refers to the capital producing sectors, and $w_{K_k qt}$ refers to the rental cost of capital produced in sector k in sector i):

$$\frac{\frac{\partial}{\partial C_{it}} V(C_{it})}{\frac{\partial}{\partial C_{jt}} V(C_{it})} = \frac{p_{jt}}{p_{it}}$$

$$\frac{\frac{\partial}{\partial L_{it}} V(C_{it})}{\frac{\partial}{\partial L_{jt}} V(C_{it})} = \frac{\xi_i}{\xi_j} = \frac{w_{it}}{w_{jt}}$$

$$\frac{\frac{\partial}{\partial C_{kt}} V(C_t)}{\frac{\partial}{\partial C_{kt+1}} V(C_{t+1})} = \beta\left(\frac{(1-\tau_{K_k qt})w_{K_k it}}{p_{kt+1}} + (1-\delta_k)\right).$$

The last equation states that the differences in the equilibrium rental costs across sectors are defined by the capital taxation:

$$\frac{w_{K_k jt}}{w_{K_k it}} = \frac{(1-\tau_{K_k it})}{(1-\tau_{K_k jt})}$$

Product markets and the general equilibrium

In the general equilibrium, the price levels match demand and supply in each sector and market. A useful way to formalize the equilibrium is to use the Shephard's lemma. It states that the marginal unit cost with respect to price changes of a production factor multiplied by the total demand of the product yields the total demand of the factor (Roe et al., 2010). Thus, it holds for each factor of production (labor, capitals, and intermediate goods of each sector) that:

$$\sum_{q}^{S,IT,NIT} \frac{\partial}{\partial w_{kqt}} [UC_{qt}] F_{qt} = m_{kt}$$

Furthermore, the volume of production in the closed service sector must match with the amount of consumption and intermediate goods of the sector. Finally, the trade is balanced and the net foreign asset position is at zero.

The calibration of the baseline growth path

The model is represented as a non-linear system of discrete time-series equations. It is solved by using a non-linear solution algorithm available in Matlab/Dynare. The solution consists of a transition between an initial steady state in 1980, and a final steady state that is gradually reached after the year 2060. With a reasonable initiation period and discounting of future consumption, the solution provides a good approximation of the infinite horizon problem's solution at the considered time interval.

The baseline growth path is calibrated to match the key structural changes in the Finnish economy. The total-factor productivity growth rates are close to their historical averages, the population growth is matched with the medium-term forecasts, and the external market is calibrated to match the structure of the exports and the share of imported products in the domestic market. The model is matched with the sectoral shifts of the consumption and value added, as well as movement of labor.

Details of the calibration:

– **Input-output structure** is based on the mid-2000s OECD input-output tables. The sectors' nominal shares of the inputs used in the production are as follows

	ICT	NIT	S
ICT-capital	0.03	0.01	0.02
NIT-capital	0.12	0.12	0.17
Service intermediate goods	0.20	0.17	0.27
Labor	0.18	0.24	0.39
ICT intermediate goods	0.35	0.02	0.05
NIT intermediate goods	0.12	0.44	0.10

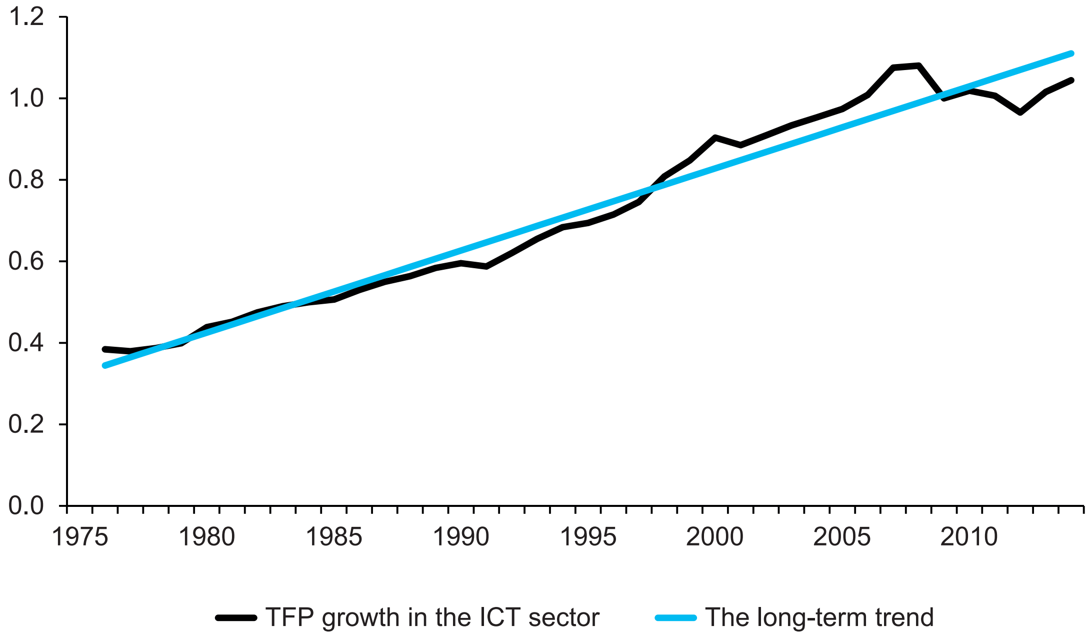
NIT-sectors own intermediate goods are gradually replaced by the service sector intermediate goods at the rate of 0.35 pps per annum in 1995–2015 due to outsourcing of manufacturing sector tasks to the service sector.

– **The sectoral total-factor productivity growth**. The growth rates are based on the average total-factor productivity growth rates of the sectors in 1980–2005. In the data, the TFPs grow at the annual rates ICT: 3.3%, NIT: 0.7%, S: 0.1%.

However, in order to better match the model with the data, we have recalibrated the TFP growth rate of the service sector to -0.5% per annum in order to better match sectoral dynamics and the relative prices. To account for the Nokia shock, we shock the model with an additional 5% increase in the TFP at the mid-2000s that is followed by 1.5 pps slower TFP growth in 2008–2012, as compared to the long-term trend. Finally, in order to match the role of the NIT sector, we use 0.1 pps slower

TFP growth than in the data. All in all, the measurement of the TFP, especially in the public sector, is extremely difficult, and therefore we are inclined to believe that our model calibration that is based on the market responses rather than the productivity statistics can provide a reasonable approximation of the TFP growth.

Figure A4.1 The TFP growth in the Finnish ICT sector and the long-term trend



Sources: Statistics Finland and own calculations.

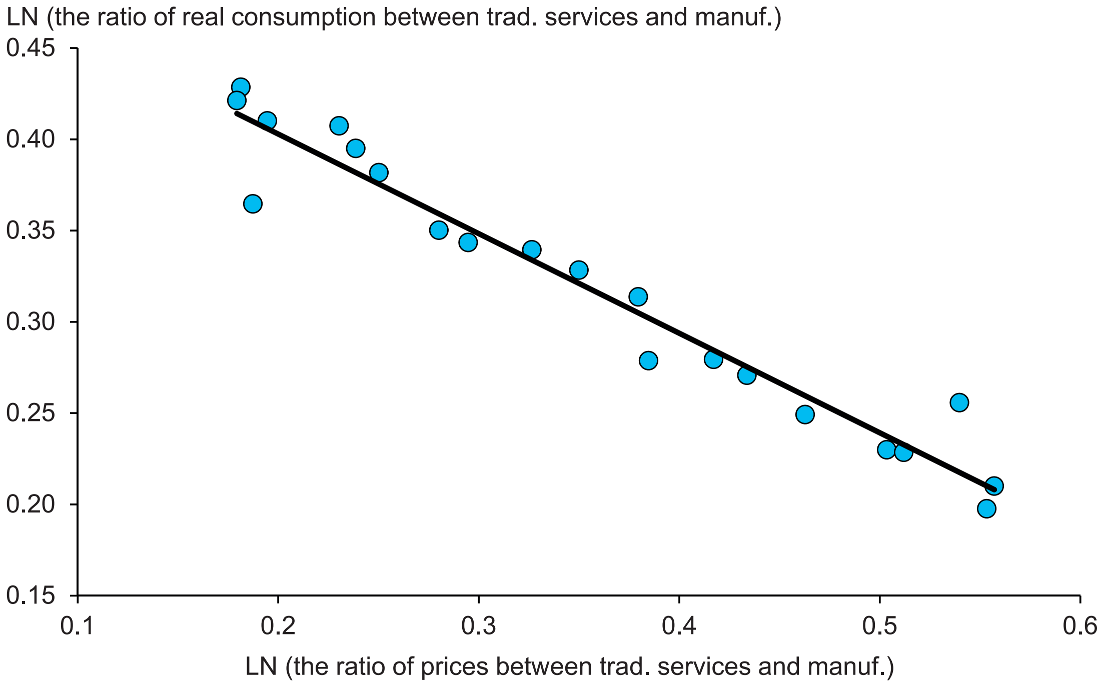
– **The depreciation rates of the capital stocks**: ICT: 24%/year, NIT:6%/year are based on the EU-KLEMS database.

– **Consumption**: The discount factor β = 0.96 and the intertemporal elasticity of substitution ρ = 2 are calibrated following Buera ja Kaboski (2009). The intratemporal elasticity of substitution ε = 0.5 and the cost shares of the sectors are based on the domestic consumption data (ω_{IT} = 0.001, ω_{NIT} = 0.163, ω_S = 0.836).

– **Trade**: The parameterization of trade is based on an estimated bilateral trade model for the year 1995, and the trends in the competitiveness and the size of the external sector are extrapolated thereafter to match the share of domestic products in the domestic final good and the sectoral shares of the exports. The elasticity of trade parameter, θ = 8.3, is based on Eaton and Kortum (2002). The external market volume grows at the rate of 5 percent per annum. The foreign ICT sector's unit costs are assumed to decrease steadily by 6% per annum. The foreign NIT sector's unit cost decrease by 2.4% per annum. It is notable that the changes in the relative price of ICT goods follows quite closely the estimates by Jorgenson and Timmer (2011).

A notable feature of the model is that the trade is assumed to be balanced. While the Finnish economy has experienced several periods of trade inbalances and there are extensive investments abroad, it can be argued that over the long-term this assumption is a reasonable one. In particular, the ratio of the Finnish gross national

Figure A4.2 A fitted line to the consumption data with the intratemporal elasticity of substitution receiving the value 0.5 (2009=1)



Sources: Statistics Finland and own calculations.

income and gross national product has been markedly stable over the long-run. This implies that while the option to invest in the foreign markets is used, there are no clear changes in the external investments behavior and thus its impact on should be more on the level of economic activity rather its growth. This assumption is more thoroughly discussed in Ali-Yrkkö et al. (2016).

– **Population and the labor force**: The labor force and the population are expected to grow at the rates forecasted by the European Commission's estimate of the potential hours and the latest long-term population projection by the Statistics Finland. In particular, the potential hours grow according to the EC potential until 2022, and thereafter the hours are growing at the same rate as the working aged population in the Statistics Finland's forecast. Finally, it is assumed that prior to the year 2008, the potential hours remain constant. Thus, we omit the role of the prior swings in the labor force that were mainly caused by the Finnish Great Depression of the 1990s.

– **Capital taxes**: In the NIT and ICT sectors the capital tax rate is set at 30 percent, while in the service sector the tax rate is 30% for private services and 0% for public services. Because we do not distinguish between private and public services in the model, we set the tax rate as the weighted average of these tax rates according to the average value-added weights of the private and public parts of the service sector in the data. In our previous analysis (Ali-Yrkkö et al., 2016), we show that under these tax rates the model matches relatively well with the actual investment rates of the Finnish economy.

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